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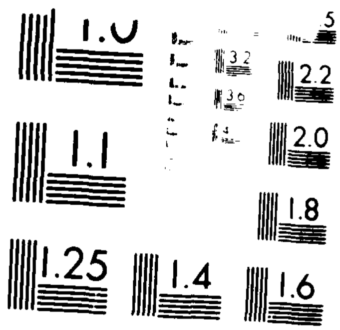
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Phase II Interim Report For:

OPERATOR ALERTNESS/WORKLOAD ASSESSMENT USING STOCHASTIC MODEL-BASED ANALYSIS OF MYOELECTRIC SIGNALS

A. Madni
C. Conaway
S. Otsubo
Y. Chu

Prepared For:
AIR FORCE OFFICE OF SCIENTIFIC RESEARCH
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This report summarizes the activities in the second phase of a three-year program of research and development directed toward the analysis and evaluation of myoelectric signals (MES) as indicators of operator alertness, and potentially workload in aircraft piloting tasks. The purpose of the study is to investigate the efficiency of stochastic models such as autoregressive (AR), autoregressive-moving-average (ARMA) and autoregressive integrated moving average (ARIMA) models in characterizing the MES under different levels of task imposed burden.

The specific objectives of this effort are:

(1) To develop/adapt state-of-the-art stochastic models for characterizing myoelectric signal patterns.

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#19 Abstract (cont'd)

(2) To investigate under controlled experimental conditions if meaningful repeatable quantitative relationships can be identified between MES patterns and operator loading.

(3) To experimentally identify muscle sites that provide reliable MES signatures.

(4) To develop methods and procedures for "tuning" the models and possibly "filtering out" pattern variations due to variables in electrode locations and individual biases.

(5) To develop guidelines for automatically assessing operator alertness level from the MES temporal signature in piloting tasks.

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1. INTRODUCTION

1.1 Overview of the Report

This report summarizes the activities in the second phase of a three-year program of research and development directed toward the analysis and evaluation of myoelectric signals (MES) as indicators of operator alertness, and potentially workload in aircraft piloting tasks. The purpose of the study is to investigate the efficiency of stochastic models such as autoregressive (AR), autoregressive-moving-average (ARMA) and autoregressive integrated moving average (ARIMA) models in characterizing the MES under different levels of task imposed burden.

The specific objectives of this effort are:

(1) To develop/adapt state-of-the-art stochastic models for characterizing myoelectric signal patterns.
(2) To investigate under controlled experimental conditions if meaningful repeatable quantitative relationships can be identified between MES patterns and operator loading.
(3) To experimentally identify muscle sites that provide reliable MES signatures.
(4) To develop methods and procedures for "tuning" the models and possibly "filtering out" pattern variations due to variables in electrode locations and individual biases.
(5) To develop guidelines for automatically assessing operator alertness level from the MES temporal signature in piloting tasks.

The three year R&D program builds on the research performed by Madni (1978, 1981) and Graupe; et al (1975, 1977). The results of these research works established the feasibility of stochastic models in characterizing sampled myoelectric signal waveforms. In particular, the work of Madni established the feasibility of stochastic models in characterizing myoelectric signals under varying levels of muscle tension and fatigue. The work reported here consists of findings and results associated with the program's first phase. The specific areas covered are: (1) the model development (2) the system implementation and (3) preliminary experimental evaluation of ARIMA model-based analysis of myoelectric signals and its relationship to task performance. Thus far the model has been implemented in Perceptronics' myoelectric data collection laboratory and preliminary experiments have been conducted to determine the diagnostic capability of the model. Work is currently underway to build on and extend the current experimental work both to provide a firm analytical and experimental basis and to develop techniques for improved data interpretation and algorithmic accuracy.

1.2 Problem Statement

The definition and derivation of objective measures for assessing workload, attentional demands or operator alertness in specific piloting tasks has been an area of investigation by several researchers for more than three decades. Myoelectric signals (MES) have been the object of study by some researchers (Kennedy and Travis, 1947; Travis and Kennedy, 1947; Kennedy, 1953) searching for a physiological indication of alertness in piloting tasks. The results of these experiments demonstrated that there appeared to be some correlation between MES properties (e.g., spike amplitude, zero crossings) and human alertness; however, the use of these properties as an indicator of alertness level was never successfully incorporated in a practical setting primarily because of the excessively high false positives in certain tasks, i.e., diminished alertness was identified in many situations when the subject was perfectly alert. One plausible explanation

for this unreliability in "answers" extracted from MES signatures is that the information content of the original MES waveform is underutilized. In other words, the reliability of features, the information content of the features, and the feature extraction process are critical to the success of the alertness/workload level discrimination process.

1.3 Major Hypotheses and Modelling Approach

Stochastic modelling and time series analysis methods have been extensively used to statistically model the relationship between the amplitude of a signal at different points in time along the entire time history. In this model, fluctuations in amplitude along the timeline are treated as a stochastic process. Stochastic models are particularly well-suited as a temporal feature extraction tool for time varying random signals. Features thus extracted retain sufficient information from the original signal and, consequently, are known to succeed in terms of feature diagnosticity in applications where purely spectral or ad hoc feature extraction methods have failed (Madni, 1978). The key hypotheses underlying the use of stochastic models as a feature extraction method for identifying operator alertness levels are that: (1) at least one model coefficient (feature) will be relatively constant and repeatable for the mental load category and task during which the signal was recorded; and (2) at least one of these nearly constant features associated with each alertness category/load condition will be sufficiently different for each load category thus allowing identification of the category.

Stochastic modelling is well-suited to modelling physiological data that possess one or more of the following characteristics:

(1) The data trace is noisy, i.e., data points show random fluctuations in amplitude and are thus amenable to being modelled as a random sequence.

(2) The classification problem is restricted to a finite, previously established number of categories.

(3) Simpler feature extraction methods such as power spectrum analysis, root-mean-square-value estimation and signal amplitude coding fail to provide good separation among the classes.

The key research problems forming the basis of this study and underlying the use of stochastic models as a feature extraction method are:

(1) The MES recorded from selected muscle groups are correlated with internal states of the human operator, e.g., alertness level or mental load; consequently, the underlying operator state can potentially be reliably diagnosed/inferred via features extracted from the corresponding MES signatures.

(2) The Feature extraction process associated with stochastic model characterization of the MES waveforms is potentially capable of "capturing" features that are both repeatable and diagnostic. Repeatability implies that there is at least one parameter in the stochastic model characterization of MES data that is constant or near-constant for each underlying level of alertness or load in a given task. Diagnosticity implies that these nearly invariant features are sufficiently different for each level of alertness, thereby allowing identification of the underlying operator state.

1.4 Background

The MES within the context of human performance and workload has been studied by various researchers over the last three decades. Within the context of human performance, the MES can be potentially used to provide a measure of either activity of the muscles or the tension of the muscles. When workload estimation is involved, data processing of some kind has to be performed on the raw MES data. This processing can range from conventional signal processing and filtering methods to temporal feature extraction and pattern analysis methods.

A number of studies have been carried out to demonstrate the practical value of MES as a measure of task workload and performance quality. Among the earliest research is that of Kennedy and Travis (1947, 1948, 1949) who found that the level of the integrated MES recorded over the supraorbital facial area was closely related to vigilance and tracking performance. Lucaccini (1968) observed similar changes in the integrated forearm flexor muscle MES during simple and complex visual tasks. He also reported that the average intrasubject correlations between MES and performance were highly significant in both tasks ($r = .21$ and $.30$ in simple and complex tasks, respectively). Stern (1966) found that integrated neck MES rose initially and fell thereafter during easier and more difficult (lower signal frequency) versions of a simple visual task.

It seems from these results that integrated MES voltage is one of the better predictors of vigilance performance, but it has not been universally accepted that MES varies directly with vigilance task performance. Eason et al (1965) interpreted their results as indicating that sympathetic activity decreases along with CNS arousal and vigilance, but that somatic activity increases as part of a compensatory process. Groll's conclusions

(1966) were essentially the same. Yet, judging from their results and the contradictory findings of others, muscle tension, like performance, may reflect both the processes underlying declines in vigilance performance and those acting to counteract.

Jex and Allen (1970) found that rectified and suitably filtered MES's recorded from the forearm of subjects showed a decrease in amplitude when subjects changed from a resting to a tracking state. These researchers also found that grip pressure was found to increase with increase in tracking difficulty. Sun et al (1976) and Stackhouse (1976) found that MES from the forehead and the forearm were correlated with task loading in a variety of aircrew tasks. Madni (1978) found a stable correlation between MES recorded during isometric contraction of the deltoid muscle at various load levels and the parameters of the stochastic models used to characterise the MES waveform.

Luciani et al (1983) at the Aerospace Medical Research Laboratory at the Wright-Patterson AFB explored the use of the Fast Fourier transform to determine operating fatigue by analysis of the center frequencies and amplitudes of the sampled power spectra. These researchers indicate that while they were successful at optimizing the acquisition and processing of the MES, reproducibility of data, especially in a dynamic environment, remained a challenging task. Kranz et al (1983) examined the frequency content of the MES when subjects performed 45-sec contractions of the thenar muscles. The median frequencies (Fm) of surface-recorded MES and compound action potentials were similar early (P greater than 0.6) and late (P greater than 0.5) in the contractions. There was a mean decrease in the Fm during contraction of 39% for 0.1). The Fm of the MES increased 11% (P less than 0.02 to 100% of maximum. Only one of five subjects showed evidence of increasing synchronization of motor unit discharge during contraction. There was no evidence that delay or dispersion of action potential propagation in terminal nerve fibers or at the neuromuscular

junction had a significant effect on frequency content. The findings indicated that the spectral content of muscle electrical activity, and its shift during contraction, primarily reflects intrinsic muscle properties.

Lindstrom et al (1983) studied localized muscle fatique in the masseter muscle with a method based on power spectrum analysis of MES. They found that under the influence of fatiguing contractions, a gradual shift of the spectral curve occurred; the rate of change was taken as a measure of the development of fatigue. The fatigue was dependent on the bite force. The existence of a threshold value of force, below which significant myoelectric fatigue changes do not develop, was shown.

Phillips et al (1983) studied quantitative electromyography techniques in evaluating the response of the neck muscles to conventional helmet weighting (physical fatigue). Their results indicate that the EMG of neck muscles can be used as a noninvasive, objective and quantitative index of the neck muscle fatigue.

Christakos (1982) conducted a study of the electromyogram using a population stochastic model of the skeletal muscle. The researcher studied the features of the electromyogram (EMG) using a population model of skeletal muscle based on the differing properties and the independent activation of motor units (MUs). He showed both analytically and by computer simulation, that: (a) The power spectrum of the EMG is determined by the distribution of filtering and firing properties of the active MUs. (b) A tendency towards a rhythmical grouping of action potentials is to be expected from a set of asynchronous MUs firing semiregularly at similar rates; the grouped electrical activity has a phase-lead over the force output of the set of about 180 degrees. He provided a unified explanation of the properties of the muscle force waveform and the electromyogram, in terms of asynchronous activity of MUs, is proposed. The explanation covers the relationship and the differences between the two signals.

1.5 Stochastic Models

Stochastic modelling (also referred to as time series analysis) has been used extensively to model the statistical relationship between the amplitude of a signal at any point in time and the preceding amplitudes along the time history (Box et al, 1970). The amplitude fluctuations along the time line are treated as a stochastic process. The future course of the process is presumed to be predictable from information about its past.

Before describing these models, the notation employed will be summarized.

- Let

  $$\ldots . X_{k-1} X_k X_{k+1} \ldots .$$

  be a discrete time series where X_i is the random variable X at time i. We denote the series by [X].

- Let μ be the mean of [X], called the level of the process.

- Let [x] denote the series of deviations about μ; that is,

  $$x_i = X_i - \mu$$

- Let [w] be a series of outputs from a white noise source with a mean zero and variance σ^2.

- Let B be the "backward" shift operator for the deviation series such that

$$\boxed{\begin{gathered} Bx_k = x_{k-1} \\ \text{Hence, } B^m x_k = x_{k-m} \end{gathered}}$$

- Let ∇ be the backward difference operator for the deviation series such that

$$\boxed{\begin{gathered} \nabla x_k = x_k - x_{k-1} = (1-B)x_k \\ \text{Hence, } \nabla^m x_k = (1-B)^m x_k \end{gathered}}$$

The dependence of the current value x_k on the past values of x and w can be expressed in different ways giving rise to several different models.

(a) Autoregressive (AR) Models. In this model the current value of x depends on the previous p values of x and on the current noise term w. Thus,

$$\boxed{\begin{gathered} x_k = a_1 x_{k-1} + a_2 x_{k-2} + \dots + a_p x_{k-p} + w_k \\ \text{or} \quad x_k = \sum_{i=1}^{p} a_i x_{k-i} + w_k \end{gathered}}$$

The series [x] as defined above is known as the autoregressive process of order p. The name "autoregressive" arises from the model's similarity to regression analysis and the fact that the variable x in an AR model is regressed on previous values of itself.

(b) Moving Average (MA) Model. In the equation for the AR model, x_{k-1} can be eliminated from the expression for x_k by substituting

$$x_{k-1} = a_1 x_{k-2} + a_2 x_{k-3} + \ldots + a_p x_{k-p-1} + w_{k-1}$$

This process can be repeated to eventually yield an equation for x_k as an infinite series in the w's. A moving average model allows a finite number q of previous w values in the expression for x_k. This formulation explicitly treats the series as being observations on linearly filtered Gaussian noise. A MA process of order q is given by

$$\boxed{x_k = \sum_{i=1}^{p} b_i w_{k-i} + w_k}$$

(c) Mixed Model: Autogressive-Moving Average (ARMA) Model. To achieve flexibility in the fitting of actual time series, this model includes both the AR and the MA terms. A (p,q) ARMA model has the form:

$$\boxed{x_k = \sum_{i=1}^{p} a_i x_{k-i} + w_k - \sum_{i=1}^{p} b_i w_{k-i}}$$

In all three models described above the process generating the series is assumed to be in equilibrium about a constant mean level. Models characterized by such an equilibrium condition are called stationary models. Functional separation of MES using this model has been tried as a means of prosthesis control (Graupe, et al, 1975).

In certain time series data, the level μ does not remain constant, i.e., the series is nonstationary. The series may, nevertheless, exhibit homogeneous or stationary behavior after the differences due to level drift have been

accounted for. It can be shown that such behavior can in certain instances be represented by an autoregressive-integrated-moving-average (ARIMA) model.

(d) Autoregressive-Integrated-Moving-Average (ARIMA) Model. The general (p,d,q) model has the form

$$\boxed{\nabla^d x_k = \sum_{i=1}^{p} a_i \nabla^d x_{k-i} + w_k - \sum_{i=1}^{q} b_j w_{k-i}}$$

where x_k is the original time series

∇ is the backward difference operator

d is the number of differencing operations performed on the original data.

p is the order of the autoregressive terms

q is the order of the moving average terms

If $\quad y_k = \nabla^d x_k$

Then $y_k = \sum_{i=1}^{p} a_i y_{k-i} + w_k - \sum_{i=1}^{p} b_i w_{k-i}$

This model is referred to as a general (p,d,q) model referring to a general pth order autoregressive dth data differencing, qth order moving average process (Box et al, 1970).

1.6 ARIMA Models in MES Characterization

The feasibility of ARIMA Stochastic Model Identification for feature extraction was explored by Madni (1978). The key elements of this study are provided in the following paragraphs.

The experimental data consisted of MES records from the deltoid muscle for different isometric contraction levels. These ranged from 0% to 100%, where 100% tension is defined as 100% of the force generated at maximum effort, not 100% of MES. The primary assumption in this experiment is that an X% run corresponds to X% of muscle tension which is proportional to abduction, and that the only muscle involved in abduction is the deltoid.

The results of the spectral analysis performed on the experimental data revealed a gradual but definite shift of power to lower frequencies with increase in muscle contraction. The total power of the signal was found to lie below 2500 Hz. The most significant shift of power to lower frequencies with increasing muscle tension was observed in the frequency band that contained ninety percent of the total power.

ARIMA models were fitted to the MES data recorded for each contraction level. The ARIMA parameters were fitted across the n trials for each contraction level. It was found that the AR terms were relatively constant for the 1%, 5% ..., 50% tension levels; however, the AR coefficients for the 100% tension level were quite different (both in sign and magnitude) from those for all other tension levels. These and other findings (Graupe, 1975) provided the impetus for exploring the stochastic modelling approach as a viable feature extraction tool.

2. EXPERIMENTAL STUDY

2.1 Overview

This Phase of the program was designed in parallel with the first series of experiments: to support the assessment derived on the "goodness" of model-derived features in terms of their relevance to operator alertness/workload levels. The primary tool used for this assessment in both series of experiments is a computer-based stochastic signal processing and pattern recognition algorithm as described in the previous sections.

In this section we will describe the behavioral issues being investigated through the use of model-based feature derivation/extraction of workload correlates. Workload correlates were primarily gathered through a task simulation resembling the Criterion Task Set (CTS) workload test battery developed at AFAMRL (Shingledecker, 1983). The task simulation paralled the initial experimental phase with exception to the perceptual task dimension due to unforeseen complications in hardware application. Each subject was presented with controlled workload tasks along central processing and motor task dimensions. As the subject performed the various tasks, the MES was recorded at the beginning, the middle and near the end of task execution. At the conclusion of the experiment, model outputs, subject performance and rating comparisons were made between levels of task loading and among the various task dimensions.

2.2 System Implementation & Experimental Set-Up

The system implementation and experimental set-up were the same as in the initial study (Madni, et al, 1984). However, since the preliminary study indicated that 60Hz interference was contaminating the myoelectric signal, we constructed a Faraday cage within the room (a grounded, wire-mesh cage)

in which a subject could sit while performing an experiment, essentially shielding him from extraneous F-F interference. Any remaining EMI was removed by using differential electrodes and by grounding the subject.

Another key issue is that the COSMOS/UNIX system tends to be quite slow because of the unavailability of floating point hardware. To this end, we are evaluating a recently released ARIMA modelling program called AUTOBJ (for automatic Box & Jenkins modelling procedure) written by Automatic Forecasting Systems, Inc. for use on an IBM PC/XT with an 8087 floating point chip. In addition to supporting floating-point hardware, the models produced in this system differ from those created by our in-house software in the following ways:

(1) AUTOBJ computes the optimal level of differencing. Our in-house system forces the level of differencing to zero.
(2) AUTOBJ can easily handle a mixed model (ARMA) with our in-house system, q is generally set to zero.
(3) AUTOBJ discards phi and theta weights of low significance.
(4) The models we obtain using our in-house system were generally AR models whose coefficients were directly comparable while the models produced by AUTOBJ had differing values of p, d and q and therefore may not be directly compared.

The problem of in compatibility can be solved by using the pi-weights for comparison rather than the model feature vector. Any ARIMA (p, d, q) model can be expressed as an infinite series of pi-weights.

With its floating-point hardware support and automated identification procedure, the AUTOAJ program could be a powerful tool for our purposes. We are currently discussing the possibility of signing a software licensing agreement with Automatic Forecasting Systems, Inc. so that we may modify the program for our application.

2.3 Experimental Hypotheses

The major effort under study is to investigate the hypothesis that perceived workload levels may be predictable by model-derived MES features. To approach this problem, three issues were investigated. The first issue involved detecting at least one ARIMA model coefficient that has a near-constant magnitude for each underlying loading/alertness level for a given subject, muscle site, and task type. To determine this, model coefficients were examined for invariance across multiple samples within trials and across multiple trials. Those coefficients that satisfy the necessary invariant conditions were then considered "reliable." Another concern was whether the features that were considered reliable were also sufficiently different in magnitude for each of the task dimensions and level of task difficulty. To investigate this problem, the features were examined across different task dimensions and levels of task demand. The third issue was concerned with whether there was high correlation and sensitivity of these features to primary task performance and subjective ratings. Various descriptive and observational statistical procedures were applied on the data to determine possible correlations between model-features, task performance and subjective ratings.

To uncover potential predictability of underlying operator workload/alertness levels from ARIMA stochastic model characterization of MES, it is vital that the selected model-derived features have both reliable and diagnostic features to infer appropriate operator state. Thus, two additional hypotheses which we have characterized as "reliability" and "diagnosticity" were investigated in this study. These hypotheses are described as follows:

- o A minimum one set of model coefficients in the ARIMA model provides invariant or near-invariant pattern values for each subject within a predetermined underlying level of mental load for a given task category, thus achieving "reliability."
- o Each reliable pattern element is distinctively unique for each level of task dimension and difficulty, providing a "diagnostic" features of predicting operator workload/alertness with model-derived MES features.

2.4 Experimental Tasks

The central concept of this study is to impose controlled workload tasks while simultaneously recording task performance measures and MES signals from selected muscle site(s). The selection of tasks and procedures was based on the degree to which they satisfy the requirements of: (1) validity and reliability, (2) flexibility and quantifiability, (3) memory, (4) mental mathematics/reasoning, and (5) choice reaction time. This set constitutes the most frequently used criteria in the literature. It also represents a subset of standardized loading tasks under development at AFAMRL. The overall criteria task set (CTS) under development at AFAMRL include the following (note that the CTS is a combination of discrete, independent task components rather than an integrated, continuous game situation such as Perceptronics' earlier simulation of a supervisory air piloting task):

(1) Perceptual tasks

- o Probability monitoring task
- o Auditory monitoring task
- o visual target search task

(2) Central processing tasks

- o Memory tasks - memory update, memory recall
- o Manipulation and comparison tasks - linguistic processing, mathematical computation, spatial pattern identification
- o Reasoning tasks - analogical reasoning and grammar
- o Planning and scheduling - flight assessment and supervisory control

(3) Motor tasks

- o Critical tracking task

A subset of the CTS was selected from existing tasks previously researched and validated at AMRL. These task dimensions included a critical tracking task and a manipulation and comparison task, paralleling the initial set of experiments with the exclusion of the probability monitoring task. Unforeseen hardware limitations impeded use of the probability monitoring task during the execution of this set of experiments. At the conclusion of the experimental procedure, exclusion of this task set was inconsequential for testing the hypotheses under investigation (See Section 3.0).

The two task elements utilized in this series of experiments are described in the following paragraphs.

Critical Tracking Task. The Critical Tracking Task is a time-honored testing procedure that progressively increases in motor task difficulty until the operator fails to control the task at hand. The level of the test at the failure point is used to define the operator's ability to maintain system stability by carefully adjusting his own control gain. Unlike the critical tracking task system used at AMRL which is "hard-wired," we implemented simulated task conditions in software,

representing the system dynamics via a set of first order differential equations and representing the task to the operator via a computer display screen. The standard critical tracking task implemented is described in Figure 2-1. The autopacer system automatically decreases the stability margin monotonically from an initial comfortable level. The rate of decrease automatically occurs as the smoothed absolute control error increases. When the task becomes so difficult that control is lost, the value of the stability margin is recorded. The task represented on the screen exhibits a center point and range of the allowable path as background, with a tracking symbol moving dynamically away from the center of the screen. The manipulation dimensions include instability level and the number of the tracking axis.

Manipulation and Comparison Task. This specific task developed under the category of Central Processing Tasks is a linguistic processing task that directs subjects to classify paired stimuli (letters, digits or words) and to indicate whether they are "same" or "different" by pressing one of two keys. The guidelines used to define "same" are physical identity (e.g., AA), name identity (e.g., Aa), category identity (e.g., Ae), rhyme (e.g., Arrange-Exchange), synonym (e.g., Ally-Friend) and antonym (e.g., Truce-Conflict). The experiments are designed to allow the same stimulus-response combination (e.g., AB-different) to occur with guidelines at quite different levels. These guidelines are stored in the computer and retrieved before the onset of the paired stimulus. The manipulation dimensions are the dominant instruction level and the type and population of stimuli.

2.5 Experimental Variables

The experimental design developed utilized a within-subject repeated-measures design which included two independent variables. The following experimental independent variables were tested:

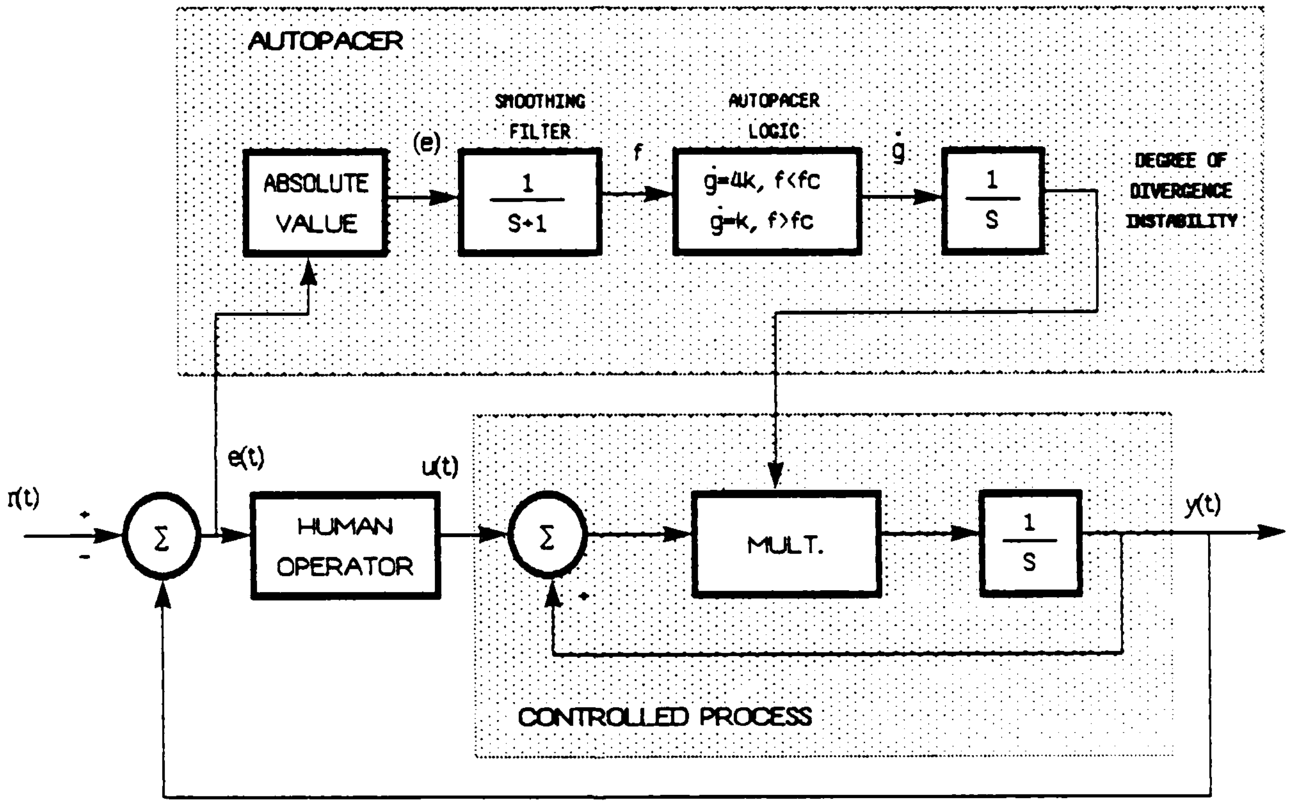


FIGURE 2-1.
SELF-ADJUSTING CRITICAL TASK IMPLEMENTATION

(1) Task category - two types

- o Central processing tasks
- o Motor tracking tasks

(2) Task loading - two levels of difficulty

- o Low
- o High

The low and high loading levels were adjusted according to the level and values given through AMRL's CTS implementation. The low loading levels were developed to provide sufficient time for the subject to respond, while the high loading level was designed to stress subject performance, but not to debilitate the subject's response accuracy. Each subject was given two trial attempts for each task set and loading level.

2.6 Muscle Site Selection

For this set of experiments, the muscle site chosen to collect myoelectric signals for the ARIMA modelling procedure was the trapezius muscle, paralleling the initial series of experiments. All subject data were collected utilizing this selected muscle site.

2.7 Subjects and Test Procedures

For this phase of the program, three male subjects were recruited from a local university. Subject ages ranged from 18-24 years old. All had at least a high school diploma and some experience with using computers. Each subject completed the formal experiment of four task variations in a balanced order.

The following procedure was conducted. Each subject was asked to read an instruction sheet (**Appendix A**) explaining the experiments that will be performed. Subjects were encouraged to ask questions as they read the instruction sheet. They were then requested to read and fill out a "personal information fact sheet" and a "consent to act as an experimental subject" form. The active electrode assembly was then attached to the subject's upper back, running parallel to the muscle fibers. A secondary ground electrode was positioned on the medial epicondyle of the subject's humerus. Both electrodes were placed on the subject's non-dominant side. (Right-handed subjects had the electrodes positioned on the left arm, and vice versa.) The subject was given an orientation and practice session lasting approximately two hours to reduce any possible learning effect that may occur during the formal experimentation. The practice session was concluded when the subject produced comparable scores on two successive trials for each task. After a 15-minute break, the actual experiment was conducted. The subject was instructed to sit comfortably upright in the chair and cautioned against moving the side of his body holding the electrodes. For each of two sittings, the subject was required to perform the tasks at the two difficulty levels. The subject was given a two-minute refresher session just prior to performing a particular task. at this time, a sampled time series of the data was displayed graphically on the screen in order to check a signal integrity. Upon task completion, the subject was asked to fill out a questionnaire in which he supplied subjective ratings and post-experimental comments. After completing this form, the subject was instructed to take a 15-minute rest before proceeding to the next task.

Each experimental task lasted 200-seconds, and subjects were submitted to two trials of all task variations. Each subject required two to three days to complete both the orientation session and the two experimental sessions. During each trial, data sampled at 1 Khz was collected in each of three 250

msec windows spaced 60 seconds apart over the 200-second trial. This data collection scheme allowed us to evaluate feature reliability both within and between trials.

2.8 Performance Measures and Subjective Ratings

The performance measures collected during the experimental trials were:

(1) Response Time - the subject response time measured from the onset of stimulus to the instant when the subject initiates an action.

(2) Response Accuracy - the response errors or incorrect actions as represented by the number of incorrect "key presses," false alarms, missed events, or response precision measures such as RMS tracking errors.

These measures were obtained after analyzing both the sampled and cumulative data. With the exception of RMS tracking error data, which were sampled four times per second, all data were sampled asynchronously.

Subjects were also requested to fill out a questionnaire after each task performed, asking them to rate on a sliding scale, (1) their perception of task difficulty, and (2) their perceived level of effort.

The results of the performance measures and subjective ratings along with the statistical and pattern analysis are discussed in Section 3.0.

3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1 Overview

Detailed results and findings for this phase of the program are presented in this section. Concurrent with the initial experiments, this experimental group demonstrates that model parameters stabilize quickly, but unlike the prior series of experiments, no obvious patterns of repeatability were observed for the first autoregressive coefficient of the model.

From the combined data of both experimental groups, results indicate no obvious trend in MES features that determine workload/alertness levels. The results of the first experimental group demonstrated possible feature repeatability with the first autoregressive parameter, but data from the second experimental group demonstrated no continuing support for this trend. Instead, must of the data appear to exhibit different levels of MES features for the same task.

The combined data from both experimental groups also exhibit no significant observed repeatability in the autoregressive model parameters. Descriptive and observational statistics are presented to describe the data gathered (see Sections 3.2 - 3.3). Thus, from current findings, the hypotheses of "reliability" and "diagnosticity" under study were not substantiated, but the results of these findings do suggest that with closer stringest experimental procedures and analyses a high degree of repeatability may be revealed not obvious in the present study.

The following sections describe in further detail the positive and negative findings identified during this phase of the program for the MES Features, Task Performance and Subjective Ratings. Further discussion is offered,

evaluating possible limitations and problems that may have affected the experimental procedure.

3.2 Positive Findings

3.2.1 MES Feature Results. MES data collected during this set of experiments revealed that no differencing was required, an indication that the signal is stationary (d=0). In addition, no moving average parameter was found to model the signal since the auto-correlation function revealed a damped sinusoid (q=0). The resulting model thus indicates an autoregress of order "p". These results are consistent with the data gathered in the initial set of experiments. This data also support evidence of possible "task shedding" as observed in the initial experimental group. "Task Shedding" was reflected by subjectivity in managing workload: people manage workload levels in different ways. In high workload situations, there is a tendency to reduce task load to a comfortable level by selectively ignoring events. This tendency to achieve comfortable workload levels may differ from situation to situation, depending on vigilance, alertness and motivational attributes at the given moment. These inconsistent results support evidence of "Task Shedding," indicating the tasks may have been measuring subject vigilance and alertness during the trials, not specific task difficulty levels.

3.2.2 Task Performance and Subjective Ratings. The following Figures 3-1 through 3-4 exhibit task performance for the three subjects under the various task dimensions and difficulty levels. From the data gathered for the Motor Tracking Task (see Figures 3-1 and 3-2), it appears that the difficulty levels produced observed differences on performance; subject errors increased as difficulty level increased. Results from the Central Processing Task (see Figures 3-3 and 3-4) exhibited less pronounced effects in Average Response Time with task difficulty levels, but a general expected trend resulted; an increase in difficulty level produced an

Figure 3-1
Motor Tracking Tasks

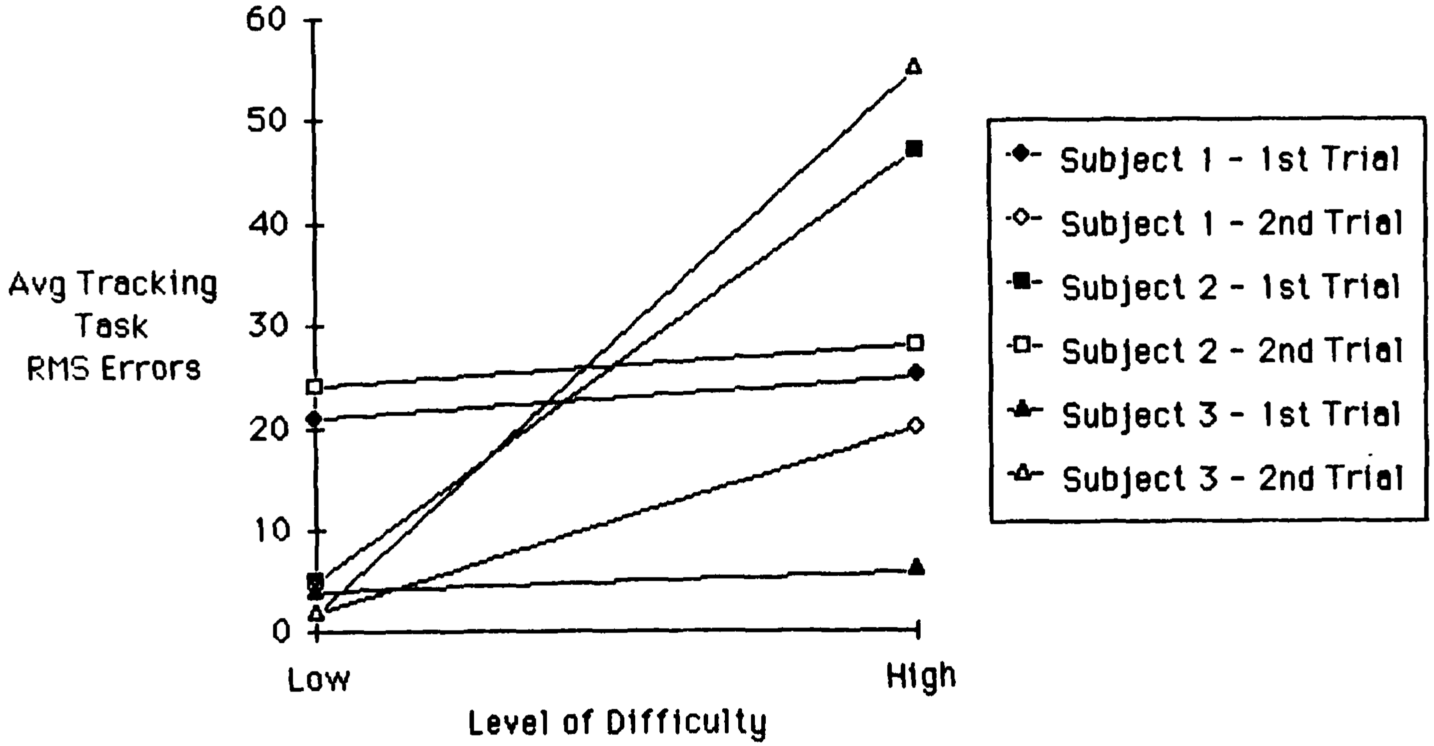


Figure 3-2
Motor Tracking Task

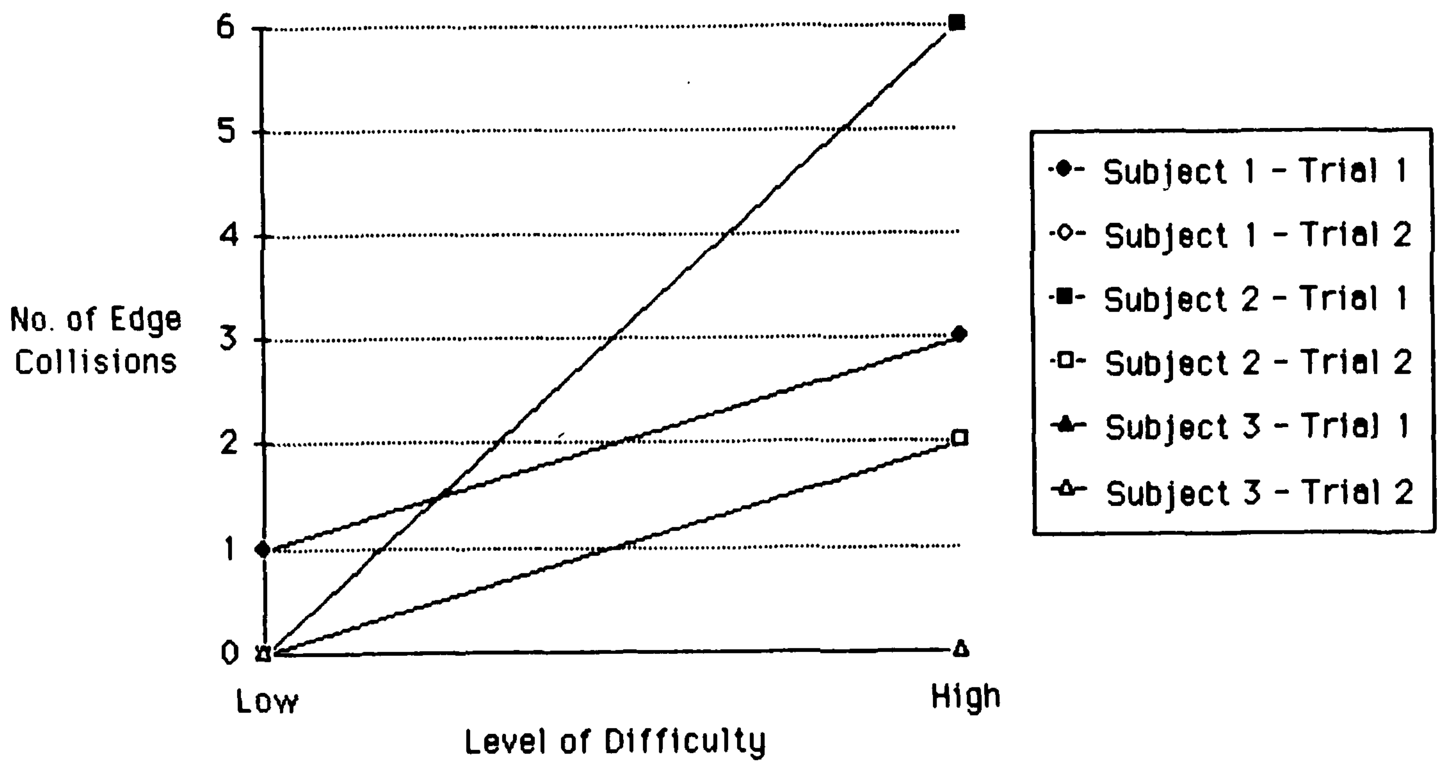


Figure 3-3
Central Processing Tasks

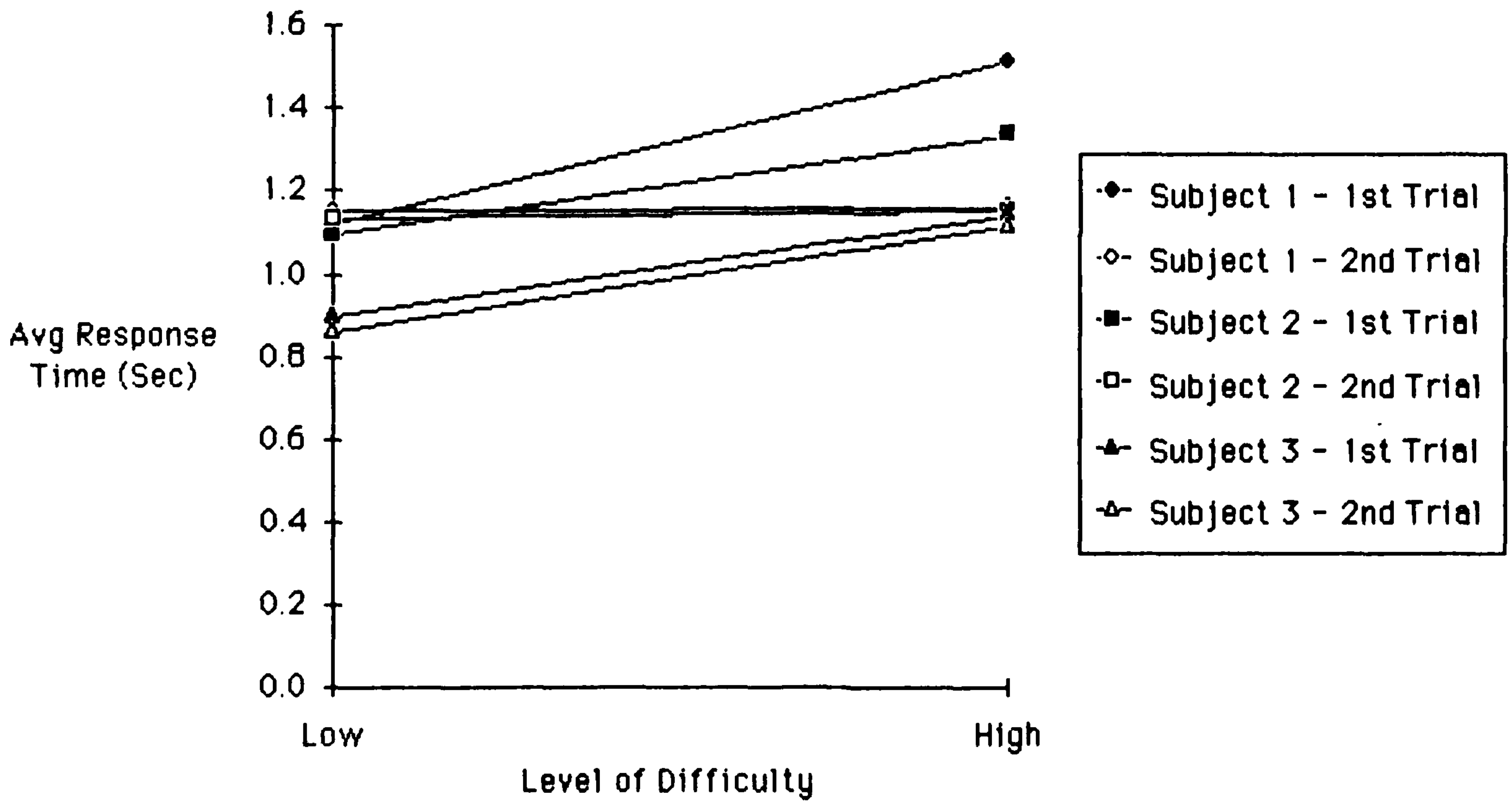
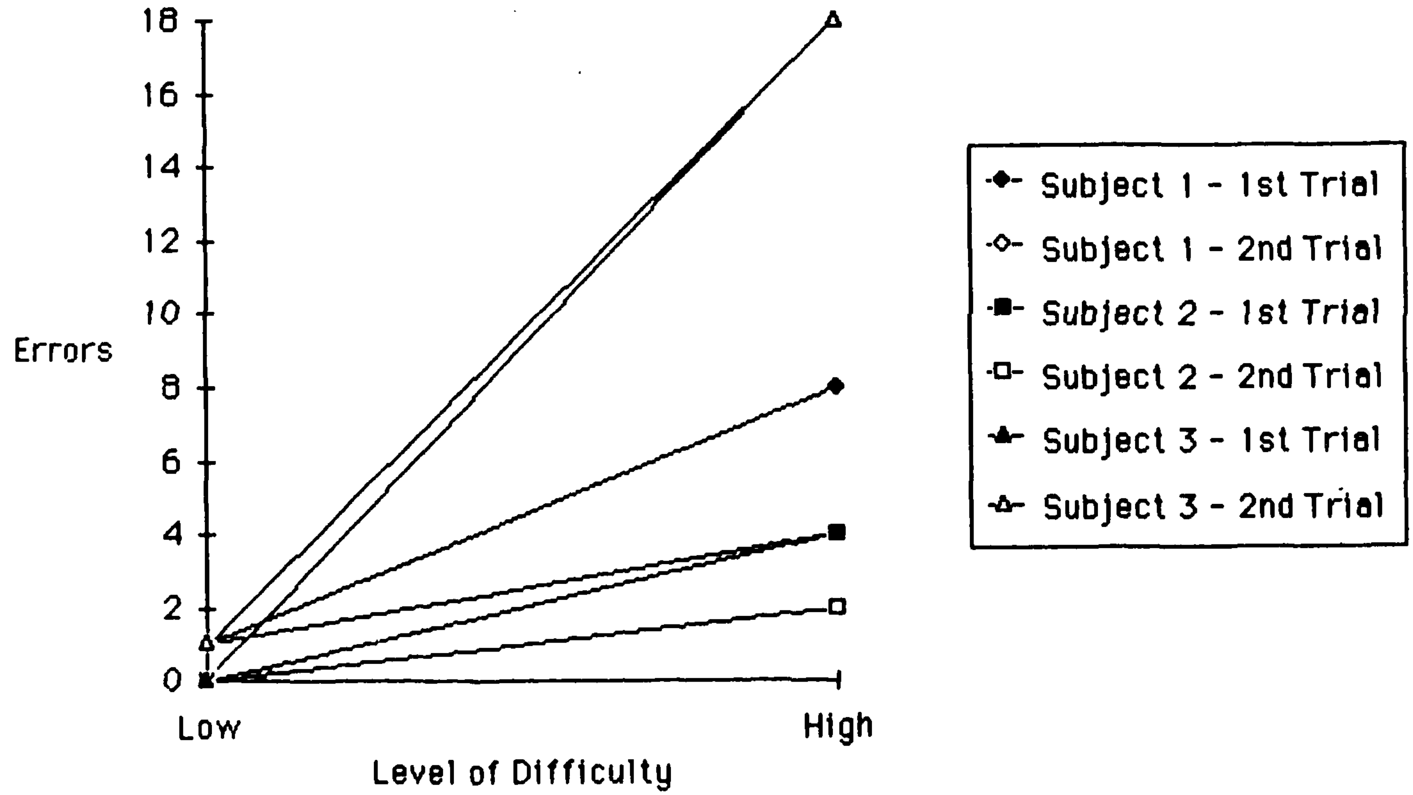


Figure 3-4
Central Processing Tasks



increase in both average response time and number of errors, similar to results gathered in the first initial experiments. The response data are supported by subjective ratings of task difficulty which showed a general increase in perceived effort and level of difficulty with the assigned workload level (see Table 3-1).

3.3 Negative Findings

3.3.1 MES Feature Results. The first AR coefficient in the first experimental group exhibited an observed relationship with task difficulty. In an attempt to duplicate comparable results with the initial set of experiments, the third recording window was analyzed to ascertain whether the first AR coefficient decreased with an increase in task difficulty. The last record was originally chosen on the assumption that most transient effects have stabilized by that point in the trial. Results gathered from this analysis did not reveal this correlation (see Figures 3-3 through 3-7), but instead revealed no consistent correlation between the AR coefficient and any subject, task, level of difficulty, or trial for the last data collection record. For purposes of comparing the last data collection "window," Subject 1 (Figure 3-5) exhibited an increase in the AR coefficient for the Motor Tracking Task for Trial 1, but then a decrease in AR coefficient for the AR coefficient for Trial 2: for the Central Processing Task Trial 1, the AR coefficient decreased, but increased for Trial 2. Subject 2 (Figure 3-6) exhibited opposite trends in the AR coefficient for the Motor Tracking Task, but a consistent increase in the Central Processing Task. Subject 3 exhibited a consistent upward trend for the Motor Tracking Task, but an opposite trend for the Central Processing Task.

TABLE 3-1

PERCEIVED LEVELOF DIFFICULTY BY

SUBJECT, TASK, LOADING LEVEL, AND TRIAL

	TRIAL 1		TRIAL 2	
	Low	High	Low	High
SUBJECT 1				
Central Processing Tasks				
Effort Level	4.0	10.5	4.0	11.2
Difficulty Level	4.8	8.7	4.5	10.3
Motor Tracking Tasks				
Effort Level	5.8	9.1	3.2	8.7
Difficulty Level	5.0	9.2	2.8	8.7
SUBJECT 2				
Central Processing Tasks				
Effort Level	3.2	7.8	9.2	8.3
Difficulty Level	1.4	2.6	3.7	3.5
Motor Tracking Tasks				
Effort Level	7.2	8.8	4.5	9.6
Difficulty Level	5.8	5.7	4.3	7.3
SUBJECT 3				
Central Processing Tasks				
Effort Level	4.5	9.1	7.5	9.1
Difficulty Level	4.5	8.8	7.7	9.1
Motor Tracking Tasks				
Effort Level	4.2	8.0	7.1	7.8
Difficulty Level	5.0	7.4	7.1	7.5

Figure 3-5
Third "Window"
Subject 1

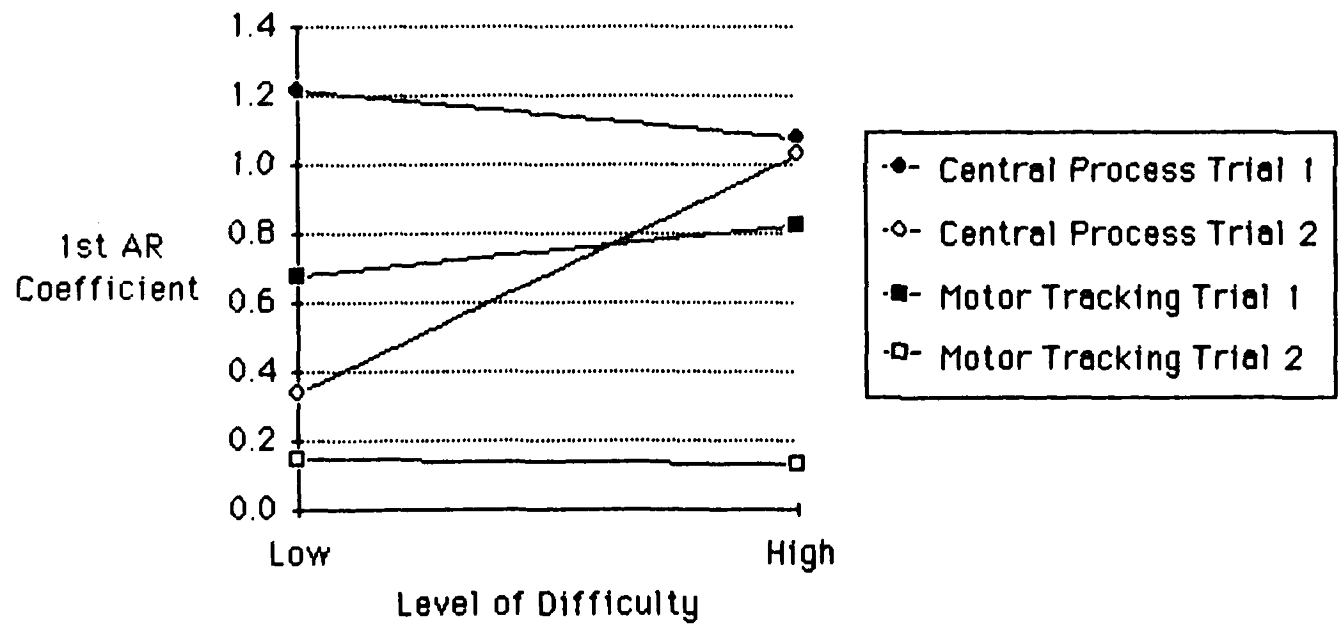


Figure 3-6
Third "Window"
Subject 2

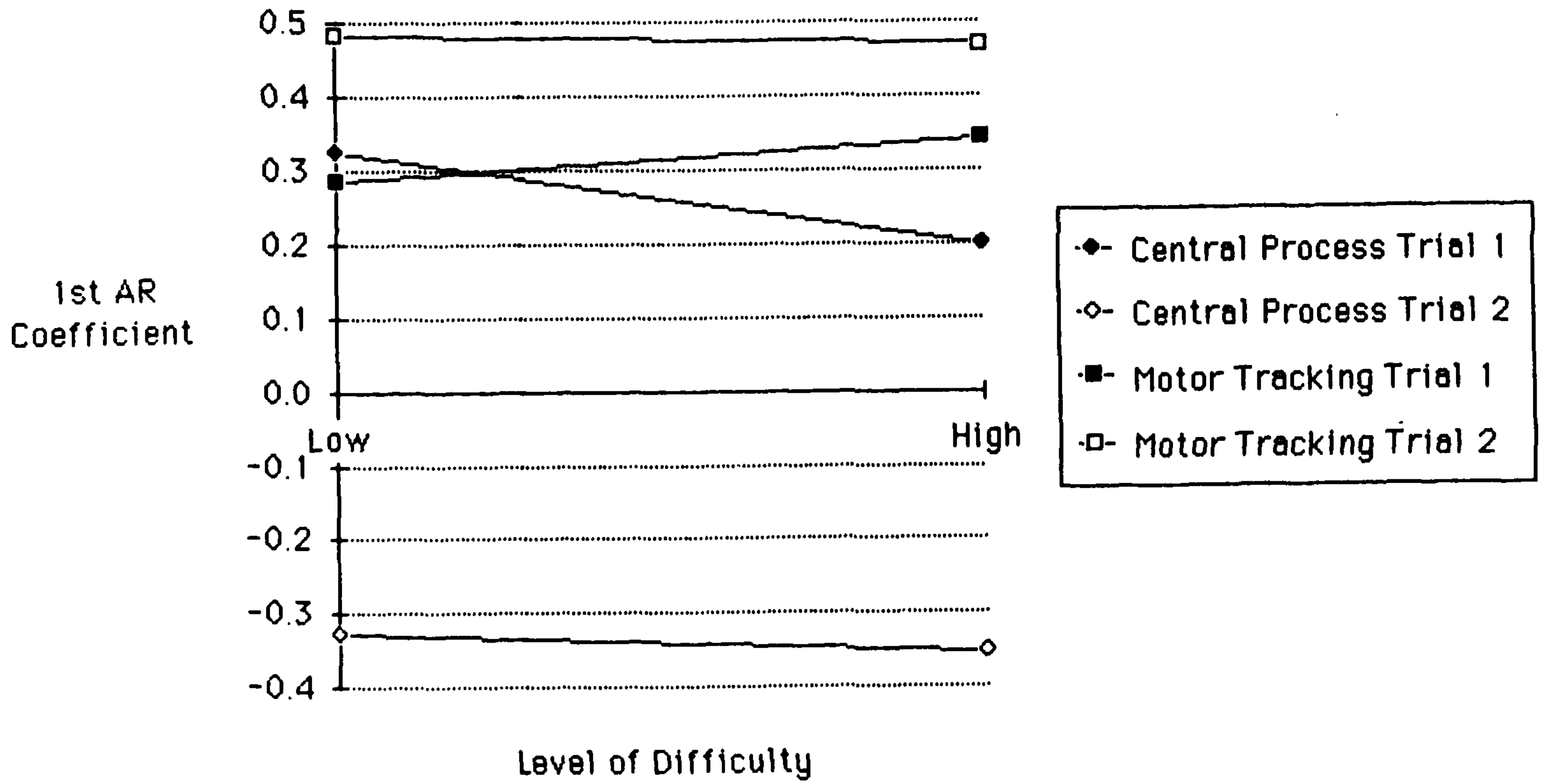
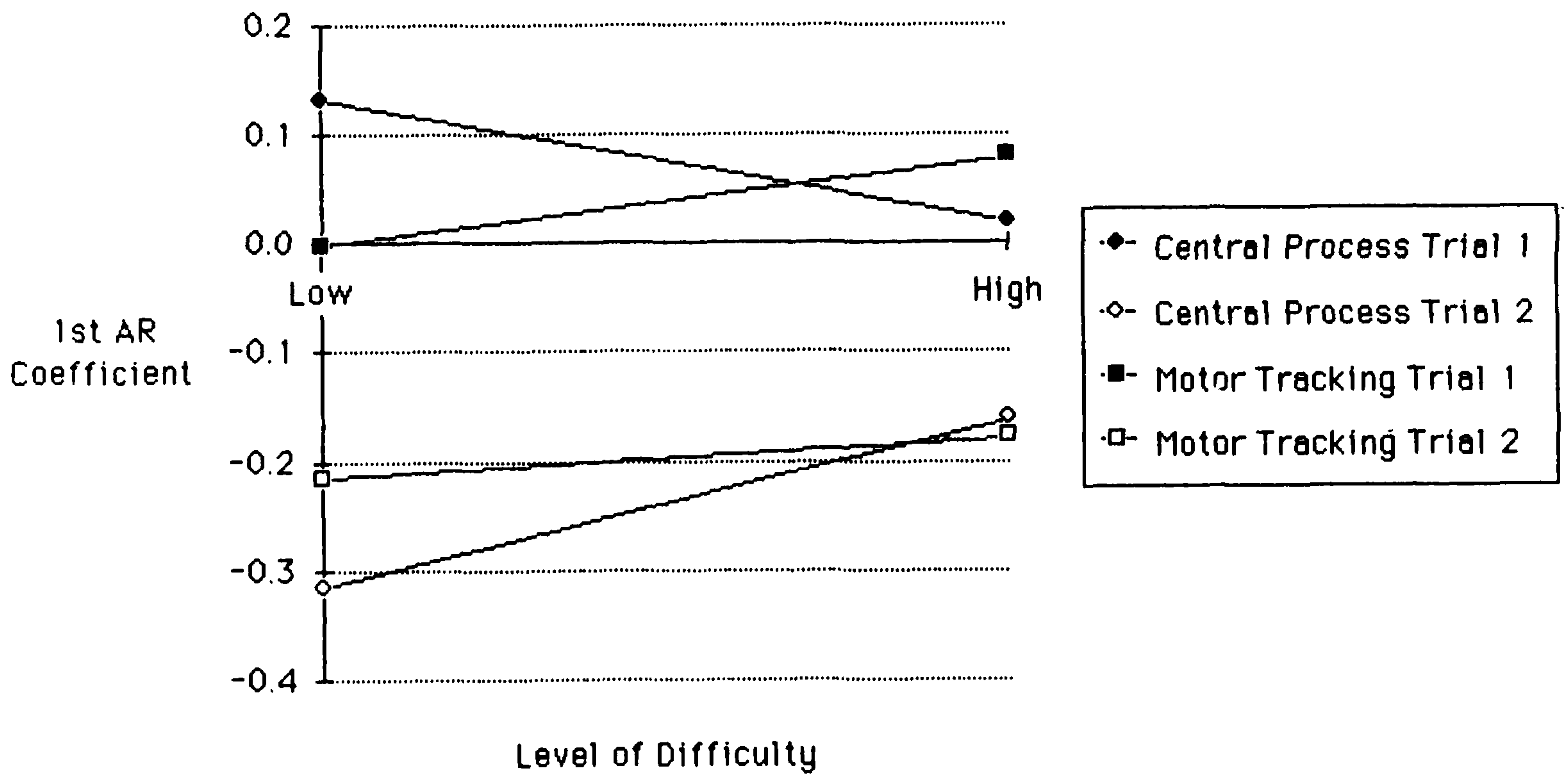


Figure 3-7
Third "Window"
Subject 3



Further correlational analysis was conducted on all data collection "windows" of the experiments. No significant correlations were found between difficulty levels and MES model features, nor were any reliable ARIMA model features evident from data collected for any of the participating subjects.

3.3.2 Task Performance and Subjective Ratings. As indicated in Section 3.2.2, task performance in general appeared to correlate with subjective ratings on difficulty level with exception to Subject 2, Central Processing Task, Trial 2. This subject perceived the level of effort and difficulty levels to be actually higher for the low difficulty level than the high level even though greater response errors occurred with the high level of task difficulty (see Table 3-1). These results were consistent with the first series of experiments. Unfortunately, although subjects perceived as assigning greater effort and concentration with increase in task difficulty, no relationship was found between these ratings and the three data collection "windows" of MES, thus no diagnosticity was substantiated.

3.4 Possible Reasons Behind Poor Results

The primary confounding problem that occurred during this phase of experimentation was the overall lack of control during the formal data collection experiments. Consistency lacked in various areas. The placement of the electrode on the subject's trapezius muscle varied from session to session, and variations in the electrode-skin interface was difficult to control over extended time periods. Even if imprecision occurred in electrode placement, relative values of the parameter under investigation over the course of a trial should be constant, but results indicated no consistency within any one trial period. This may have been due to subject movement during data collection, improper interface, or even improper muscle choice for the tasks performed.

Another factor that may have influenced the data involves the insensitive measure gathered from the subjective ratings. Task performance results were always available to the subjects immediately after performing the task. This knowledge have have influenced their subjective ratings on the questionnaires; one subject may have noticed that the number of errors was high when compared to the other difficulty level, thus he may have perceived the task to be more difficult, than if he was not given the opportunity to see performance results at all. With the influence of this confounding factor, it is possible the established difficulty task levels may not correlate with perceived effort/attention indicated on the questionnaires.

A third influencing factor involves the general control of hardware placement and extraneous environmental influences. Glare from the screen, the angle of vision from the subject's eyes to the screen, general noise from the surrounding area, heat generated from the computer and other various hardware apparatus, and placement of the chair were all variables that may have impeded the task performed and interfered with MES data collected.

These results may have seemed spurious and unrelated to the hypotheses set forth, but due to the subjective perception of workload, these results may in fact be correlated with subjective workload, not obviously detected. A subject's emotional state fluctuates continually, and may be reflected in different levels of muscle tension. Fatigue, concentration, and motivational levels also differ from situation to situation, and possible from task to task. The subjectivity of workload may be the underlying cause of this fluctuation, whereby the subject increases vigilance with some increase in difficulty, but at another time he may either become fatigued, bored, or may lose concentration with the same task. Another explanation of the underlying subjective perception of load as indicated in the first series of experiments relates to the phenomenon of "task shedding";

subjects reduce mental workload to a manageable level they feel comfortable with. One trial may be conducive to lower vigilance than another trial due to changes in subjective workload. This may be a possible explanation for the spurious results exhibited by the three participating subjects in this effort (Figures 3-5 to 3-7). The limited number of subjects participating in the experimentation may have also biased results; they may have been an irrepresentative sample of the population. With an increase in the number of participating subjects, it is possible that significant correlational relationships would have evolved from the data.

If the results were due to subjective perception of workload, the AR coefficient may be related to motivation or concentration levels perceived by the subject rather than the specific task difficulty levels performed in the experiment. Due to the nature of the tasks and the unforeseen difficulties with the experimental hardware, subjects were required to perform the task repeatedly. All task demands did not fluctuate but remained constant, demanding a steady state of response from the subjects. This may have caused subjects to become bored with the task, demanding responses at constant time intervals and a constant rate; subjects may have performed with high vigilance for a task at one time, then may have performed the same task with low alertness and concentration at another time.

The muscle chosen for data sampling may been inappropriate. The preliminary determination for muscle site selection was performed on one subject. The result of this preliminary determination may have been unreliable, and analysis of further subjects may have uncovered other possible muscle site selections to be more appropriate determinants for our hypotheses under investigation.

The data collection "windows" may have also been inaccurate: both the duration of the windows and the periods during task performance when the MES data windows were collected. The data gathered only reflect the subjects' responses during that small 60-second period of time, and may not have reflected the true difficulty, stress, or workload perceived by the subjects for that particular task. For instance, for one task a subject may have been waiting for another question to be generated by the computer while the data collection was occurring, thus resulting in an anticipatory response; at another task, data collection may occur during a period when questions were displayed to the subject, thus resulting in another stressful response. These data collection windows may not have reflected consistent expectancies in task and difficulty levels.

Additional limitations in data collection hardware were apparent. No method available allowed the integrity of MES to be tested: the physical construction of the electrode used also inhibited data collection from the frontalis and temporal muscles, two muscles previously correlated to mental-stress activity; and high speed, multi-channel data conversion was not available with the UNIX controlled acquisition board.

3.5 Possible Solutions

To alleviate some of these problems, modifications in the experimental design procedure are required in an effort to control the extraneous confounding variables that affect data collection and subjective ratings. An increase in the subject pool would facilitate greater power into the experimental design; subjects should not be allowed to view their responses during the formal experimentation, in order to avoid influence in their response; the placement and choice of electrodes should be as consistent as possible, from session to session and from subject to subject; and environmental influences should be maintained constant, as angle of vision, noise, heat and glare from the computer screen.

The tasks developed may have not been appropriate. Subjects may have become bored with the low difficulty level of the tasks, thus exhibiting low alertness levels. These tasks should be stringently pretested for appropriateness to difficulty levels: low difficulty levels should not be too easy to generate boredom, while high difficulty levels should not debilitate subject response to the point of giving up. We are presently investigating experimental tasks used in previous mental workload studies to determine their relevance to our current study.

The MES data collection hardware must be flexible and accurate to gather appropriate expected data. Currently it is unknown exactly what responses are requested during the data collection periods. Possibly an incorporation of an analog recording display would test the integrity of the MES. The additional use of more suitable electrode apparatus would offer flexibility in collecting MES data from other desired muscle groups, and an upgrade in data acquisition systems would aid in the collection of accurate MES data. This flexibility along with closer measurement of time and rate of error may help to determine diagnosticity in MES signals with workload/alertness levels.

4. NEW DIRECTIONS

4.1 Revised Experimental Procedure

The future experimental design and procedure should incorporate two general conceptualizations: a development of an integrated task dimension, utilizing primary task categories as perception, cognition and motor task ability; and the incorporation of accurate measurement techniques as MES data collection during predetermined windows, number of errors during preset time period, and subjective ratings. Together with more powerful and more control of experimental variables, there is a higher probability that reliability and diagnosticity in MES signals to workload/alertness levels may be achieved. Below is a detailed description in these conceptualizations that suggest possibilities for future experimentation.

The integrated task dimension to be developed will utilize the application of an actual, validated simulation currently applicable to pilot workload situations. The reason behind this utilization is the notion of applying directly the benefits uncovered from the experimental results to an actual real life situation. The CTS simulations applied in the first phase of this program (which involve separate tasks of perception, cognition and motor response tasks) may be useful in the laboratory, but may be difficult to apply to any situation that will occur outside of the laboratory. For example, a simulated task dimension may involve the incorporation and integration of pilot tasks as perceiving changes in flight display (perceptual task), moving an input/output device as a joystick to maintain flight stability (motor response task, and plan flight control and assessment (cognitive task). Combining these various tasks would simulate pilot workload to a closer degree, resulting in the establishment of accurate stress/workload levels that would parallel true situations. Realistic tasks require operators to change from tasks to task when situations demand

it, to react to emergency situations quickly, and to maintain stable responses over time. In this regard, if significant findings resulted in MES correlation with workload/alertness levels, these levels would be predictable and diagnosed, adding the direct capability to reduce or increase demands on the Air Force Pilot who performs this function when needed.

The utilization of a new integrated task set will also be utilized to understand and control the influence of subjective perception of load. The application of various workload situations will be closely examined and evaluated to determine possible operator response and perceptions to each situation. At those selected events, MES signals will be collected to ascertain any possible correlational relationships with perceived workload/alertness levels.

Alongside this integrated task dimension conceptualization is the use of data collection that will reflect detailed levels of input response from the operator and output generated by the simulated task. Each data collection window will be triggered subsequent to selected situations, whether it be a question to respond to (moderate stress), an emergency situation to act upon (high stress), or a situation when nothing is expected (low stress). With this implementation, it will be possible to associate specific difficulty expectancies with responses from the subjects. With the detailed evaluation of task integration and measurement, it will also be possible to determine combination of tasks that may induce higher stress levels than other combinations. Also the rate of errors that occur may be collected; more errors occurring within a preset period may be an indication that a higher level of stress/workload may be perceived by the subject, than at other times when errors may be occurring at a constant rate.

Additionally, flexible MES signal collection windows may be required. For instance, perceived workload may differ for the same task condition, depending on the subjectivity of the operator at any given moment. High stress may be observed by a sudden change in strategy, error rate, or general instability in reactions. These inconsistent responses may occur at the same task session, and under the same task situation. When these situations occur, MES signal collection would be desirable.

With the alleviation of extraneous confounding variables that occurred in this initial phase of the program, and with the implementation of the additional conceptualizations as described above, future experimentation is viable with possibilities to uncover model-based feature extraction of workload correlates that may be directly applicable to the Air Force domain.

4.2 New Data Acquisition Techniques

A fundamental problem with the data collection phase of the experiment is that we currently have no way to check the integrity of the myoelectric signals being digitized. We are therefore investigating the possibility of integrating an analog recording/display device (i.e., strip-chart recorder, long persistance monitor) into the system so that we may in real-time, view the analog signal being sampled.

The physical geometry of the electrodes we are currently using preclude our acquiring myoelectric data from the frontalis and temporal muscles, two muscles which in previous studies have shown mental-stress related activity. Switching to a more standard type of electrode which will allow us to collect myoelectric data from these muscles will require the purchase or construction of a precision, low-level myoelectric signal amplifier.

We've also found that our data acquisition board running under UNIX control, doesn't allow for the high-speed, multi-channel, data conversion we require. Some of the new IBM PC/XT based data acquisition systems (i.e., Data Translation, ARCO Systems) allow 12-bit successive approximation conversion at rates up to 27,500 samples per second on multiple channels. Because most of these systems include D/A in addition to A/D conversion, they would enable us to reconstruct the sampled myoelectric waveform and compare it to the original. We are presently investigating the features of these systems to see if they might increase the overall flexibility of our overall system (e.g., allow us to investigate the effect of sampling rate and sampling window size on the ARIMA coefficients and to optimize the acquisition parameters).

4.3 New Data Analysis Techniques

No floating-point hardware is currently available for the COSMOS/UNIX system. We therefore are currently evaluating a recently released ARIMA modelling program called AUTOBJ (for Automatic Box and Jenkins modelling) written by Automatic Forecasting Systems, Inc. for use of an IBM PC/XT with the 8087 floating-point chip. The models produced by this system differ from those created by our in-house software in the following ways:

(1) AUTOBJ computes the optimal level of differencing. Our in-house system forces the level of differencing to zero.

(2) AUTOBJ can easily handle a mixed (ARMA) model. With our in-house system, q is generally set to zero.

(3) AUTOBJ discards phi and theta weights of low significance.

(4) The models obtained using our in-house system were generally pure AR models whose coefficients were directly comparable while the models produced by AUTOBJ had differing values of p,d,q and therefore may not be directly compared. This incompatibility problem can be resolved by using the potential model (whatever it might be) to generate pi-weights for comparison rather than the model feature vector.

Any ARIMA (p, d, q) model can be expressed as an infinite series of pi-weights as follows:

Take the general ARIMA (p,d,q) model $[1-\Phi_p(B)][1-B]^d Z_t = [1-\theta_q(B)]\, a_t$. Divide both sides by $[1-\theta_q(B)]$ to yield

$$\frac{[1-\Phi_p(B)][1-B]^d Z_t}{[1-\theta_q(B)]} = a_t.$$

The resulting polynomial coefficients of the potentially infinite order polynomial in B represent the pi-weights. If q=0, then the polynomial in B is of order (p+d) and if d is also zero, the polynomial is of order p and identical to the $\phi_p(B)$ polynomial. It is important to truncate the pi-weights after some number such as (p+d+q) to parsimoniously represent the time series.

With its floating-point hardware support and automated identification procedure, the AUTOAJ program could be a powerful tool for our purposes. We are currently discussing the possibility of signing a software licensing agreement with Automatic Forecasting Systems, Inc. so that we may modify the program for our application.

4.4 Rationale for Changing Approach

The primary rationale for implementing improvements and changes to the research approach stems from the lack of experimental control evident in this current initial phase of the study. It is unknown whether the results gathered from the initial experimental groups would have been significant if stringent experimental controls were applied. The results may have been due to extraneous environmental variables rather than effects applicable to the hypotheses under study.

The tasks also required constant, repetitive actions from the operators, thus assuming constant performance throughout any one task. With the suggested use of an integrated task dimension, correlational accuracy of realistic task workload to MES model-features may be achieved, instead of correlating unrealistic repetitive responses required by the current task set to MES model-features. This implementation will support the realization that users do not react to a situation at a constant pace or workload rate, but change and fluctuate during performance, sometimes stabilizing, and sometimes fluctuating, depending on the current subjective perception of workload.

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APPENDIX A

SOFTWARE SPECIFICATIONS

Software Specifications

Overview

There are three packages employed in the MES acquisition and analysis process. Two are used during the performance of the experiment and one is used during the off-line analysis of the MES data.

The two packages used in the performance of the experiment consist of one package for the COSMOS system and one for the Apple. The COSMOS system is used to control the experimental parameters and collect MES data from a subject through the electrodes and A/D board. The second package is used on the Apple IIe to control the presentation of graphic inputs to the subject, record subject responses, and to print a subject performance record.

The third package is comprised of the ARIMA modelling routines and performs analysis of the previously collected MES data in batch mode under control of the experimenter. The experimenter can enter up to 25 files containing MES data records and the package will compute either the autocorrelations and partial autocorrelations of the MES data (step one) or compute the final ARIMA coefficients (step two) for each data record in the selected file.

The two packages running on the COSMOS system are discussed in section A.1. Section A.2 contains specifications of the Apple software.

A.1 Data Acquisition and Analysis Packages

Both packages running on the COSMOS are written in C. The first package which controls the experiment and data acquisition, consists of 4 routines and uses the Analog-to-Digital converter driver. The high-level routine MES-EXP controls the package. It opens up a device communication channel with the Apple and calls two lower level routines (usr-select and set-up) to get session parameters and set up data files for MES data collection. When the operator instructs MES-EXP to start an experiment, a timer is started and the third routine (collect), is called on to collect data at experimenter specified intervals. MES-EXP instructs the Apple to stop generating graphics and recording responses, and to generate a summary report when the session is finished.

The routine usr-select allows the user to specify experiment type, level of difficulty, trial number and the A/D channels used to collect data. By selecting a combination of 1 to 4 channels, a sampling rate of 2000, 1000, 500, or 250 Hz can be selected. The experimenter also supplies the period between sampling windows and the total session length. The data from each window is stored in a separate record within each data file.

The routine set-up allows the experimenter to specify particular files to receive the data from each A/D channel. A header describing the contents of the file may also be supplied.

Finally, the routine collect is responsible for controlling the A/D and collecting data. Currently, 500 data points are collected per window.

The other package running on the COSMOS contains a batch processing routine and the ARIMA routines. The batch processing routine, MES-BATCH, allows the experimenter to control the analysis process. The experimenter can select up to 25 MES data files for analysis. He is then asked which stage

of the ARIMA identification process he would like performed on the specified data files. If the first stage, the identification phase, is specified, the operator is asked the maximum level of differencing desired. If the second stage is specified, the operator is asked to input the values of p, d, and q for each record in each of the specified files.

There are three routines used for the ARIMA analysis -- one for each step of the process. The top-level routine for step 1 is USID which controls the process of computing autocorrelations and partial autocorrelations for an MES data record. These autocorrelations and partial autocorrelations are used by the experimenter to estimate p, d, & q. The top-level routine for step 2 is USPE which controls the calculation for the initial estimates of the autoregressive and moving average parameters. The top-level routine for step 3 is USES which controls the calculation of final autoregressive and moving average parameters. The function of each routine in the ARIMA subsystem is given in Table A-1.

Calling Hierarchies

The calling sequences for all routines are given in Figure A-1.

Experimenter Interface

(1) Performing the Experiment. The experimenter must first boots up the Apple IIe experiment control system. The Apple IIe then waits for a run command to come over its RS-232 serial interface. After booting and logging into the 68000 system, the program MES-EXP is executed. The following messages then appear on the COSMOS system.

TABLE A-1

SUBROUTINES AND ASSOCIATED FUNCTIONS

This list contains the subroutines used by a system with a short statement of function for each routine.

USID	- aids in selection of p, d, & q
diff	- differences a series
mean	- gets the mean of a series
acov	- gets autocovariances
stera	- gets standard errors of autocorrelations
pacor	- gets partial autocorrelations
USPE	- gets initial estimates of and
atoprm	- gets initial estimates of
modcov	- modifies covariances
movarvr	- gets initial estimates of
whtnos	- gets initial estimate for white noise variance
nwtrph	- Newton-Rapson subroutine
gttmat	- gets immediate matrix, tmat, for Newton-Rapson algorithm
matinv	- gets inverse of a matrix
mltmv	- multiplies a matrix by a vector
USES	- gets maximum likelihood estimates of and
calcas	- calculates conditional residuals
ssqr	- gets sum squared of a vector
calcax	- calculates matrix (see 1.4)
calcagd	- calculates matrix a and vector g (see 1.4)
newest	- gets newest estimates of and
check	- checks sum squared of residuals
covest	- gets covariance matrix of estimates
calcscc	- gets standard errors and correlation matrix
rsdac	- gets residual autocorrelations
calchi	- gets chi-square statistic and degrees of freedom
cnchk	- convergence check for Marquardt algorithm

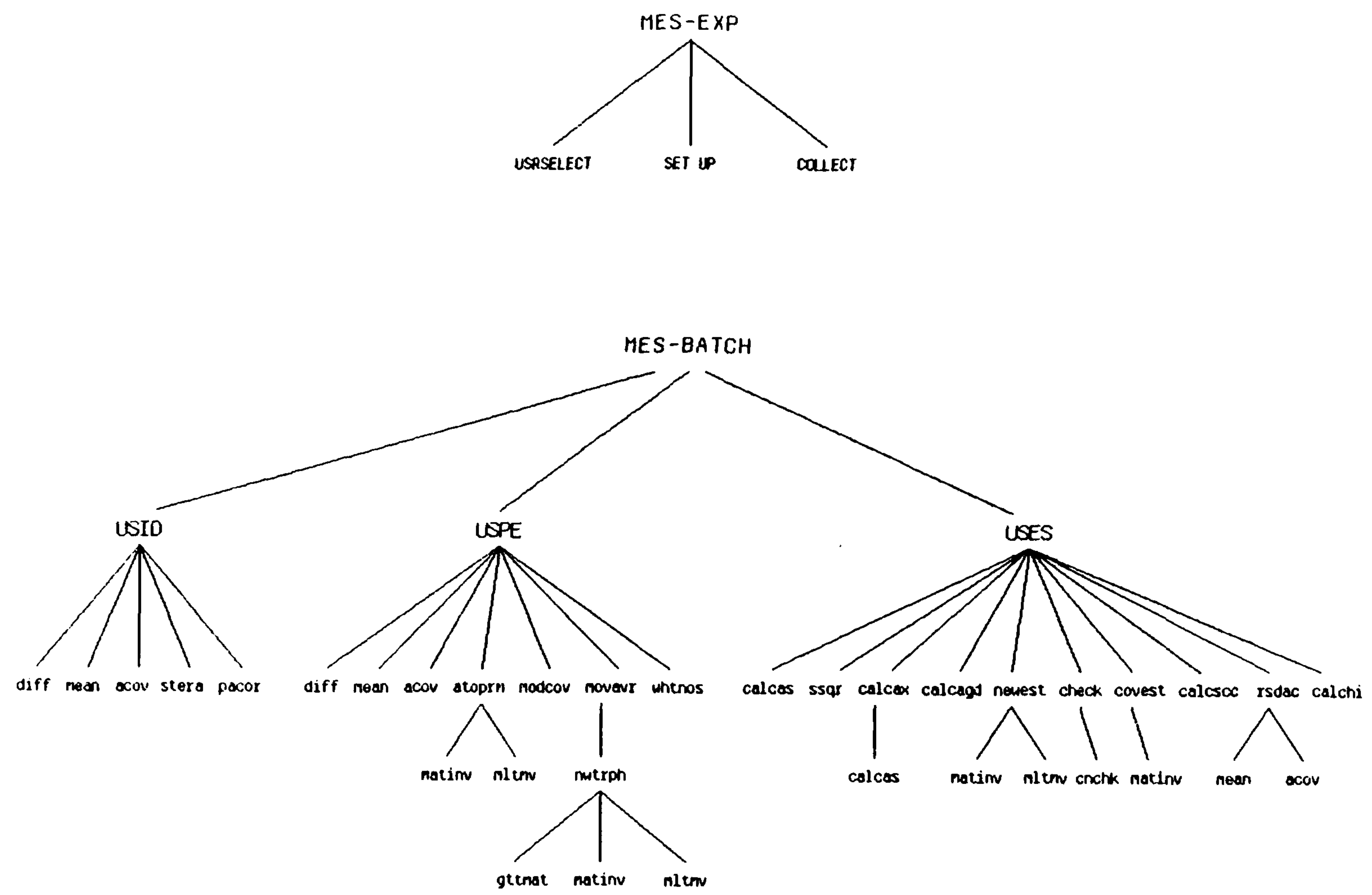

FIGURE A-1.
CALLING HIERARCHIES

MYO-ELECTRIC SIGNAL COLLECTION EXPERIMENT

TYPE TASK TYPE:

'p' - PERCEPTUAL
'c' - CENTRAL PROCESSING
'r' - MOTOR RESPONSE

The experimenter then responds with the character for the desired task. The system then prints:

TYPE TASK LEVEL:

'l'-LOW
'h'-HIGH

The experimenter responds with the character for the desired level of difficulty. The system next types:

TYPE TRIAL NO., '1' or '2'

The experimenter responds by typing '1' or '2'. The system then types:

TYPE EACH A/D CHANNEL USED SEPARATED BY BLANKS
TYPE '-1' FOLLOWED BY RETURN TO TERMINATE

The experimenter types the channels to be used separated by RETURN'S and followed by -1. The system then types:

TYPE PERIOD OF SAMPLINGS IN SECONDS

The user responds with the desired value. Then the system says:

TYPE SESSION LENGTH IN SECONDS

The experimenter responds with the desired value. The system then prints:

TYPE DATA FILE NAME FOR A/D CHANNEL __

The experimenter responds with the file name. The system then responds with:

TYPE HEADER FOR THIS FILE, TERMINATE WITH '*' RETURN

The experimenter types in his header and the file, header sequence is repeated for each A/D channel specified by the experimenter. After the last file and header is specified, the system responds with:

PLACE AND POWER UP ELECTRODES
READY APPLE
PRESS RETURN TO START EXPERIMENT

When both the experimenter and subject are ready to begin the session, the operator presses the return key to initiate the experiment. A run command is then given to the Apple and the two systems begin operating synchronously. When the previously defined session length is reached, the system prints out "EXPERIMENT TERMINATED" on both screens.

(2) Batch Processing ARIMA Analysis. The experimenter runs the ARIMA analysis of the MES data after the experiment has been performed and the data collected. He normally runs the experiment in two stages for a group of MES data files. First he identifies p, d, & q for any or all of the records in each file. Then he runs the system again to find the final

autoregressive and moving average parameters for each record.

When the experimenter runs the 68000 routine MES-BATCH, he sees:

EMG ANALYSIS PROGRAM

TYPE CURRENT DATA FILE NAME

The experimenter then types the current file name. The system then says:

TYPE 'Y' IF YOU WANT TO SPECIFY p, d, & q; OTHERWISE, TYPE 'n'

The experimenter responds. If he types 'y', the system says:

IF YOU WANT TO PROVIDE p, d, & q FOR RECORD 1, TYPE 'y';
OTHERWISE TYPE 'n'

The experimenter responds. If he types 'y' the system prompts as follows with the experimenter's responses underlined:

p = ______
d = ______
q = ______

The system then asks him if he wants to specify p,d, & q for record 2, etc. up until the user types 'n'. The system then says:

TYPE 'y' IF YOU WANT TO SPECIFY ANOTHER FILE; OTHERWISE, TYPE 'n'

If the experimenter responds with 'y', the system types out:

TYPE CURRENT DATA FILE NAME

and the process repeats. When the experimenter finally says he doesn't want to type another file, the system types:

FILES TO BE USED ARE:
(Followed by experimenter specified files.)

The system then prints:

TYPE ONE OF THE FOLLOWING COMMANDS:

'i' - IDENTIFY P, D, & Q
'e' - ESTIMATE PARAMETERS

The experimenter types the desired command and the batch mode analysis program begins writing the results to either a file or the printer.

A.2 Experimental Control Package

The Experimental Control package, implemented in GRAFORTH on the Apple IIe is capable of supporting three separate experiments:

(1) Perceptual experiment.
(2) Control experiment.
(3) Motor response experiment.

(1) Perceptual Experiment. This experiment tests the subject's ability to monitor and respond to a series of ongoing events, on up to four separate displays. This emulates the events displayed to the pilot on aircraft gauges.

Each display consists of a horizontally graduated scale with an initially centered arrow. The arrow oscillates back and forth around the mean using a preset event scheduler which eventually drives the mean off center. The subject is expected to keep the arrow mean centered using dedicated keys. The performance of the subject is measured according to his response time to each individual event.

The arrival time of the event is in accord with a Poisson distribution on a Pre-Set Schedule. There are two levels of difficulty implemented on this experiment.

The subject is presented one or four sets of horizontal scales and oscillating arrows. He responds to a change in the mean of oscillation for any or all of the arrows by pressing the correct arrow key on a dedicated keypad (Figure A-2).

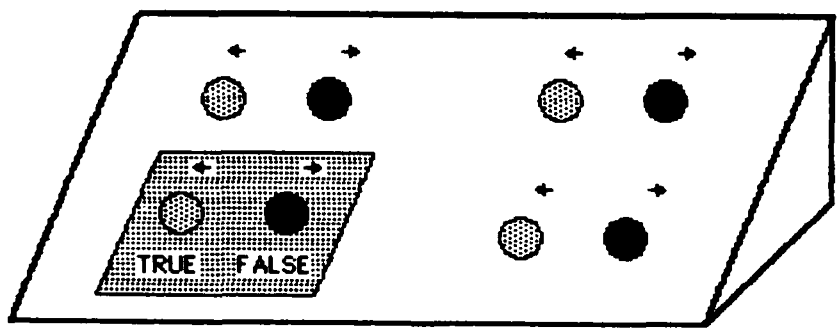

FIGURE A-2.
RESPONSE KEYPAD

Each pair of keys corresponds to the scale and arrow located in the same quadrant on the screen. The correct response to a mean shift is to press the arrow key in the direction in which the mean has shifted.

Performance Evaluation. When an event occurs (i.e., mean about which the arrow oscillates in accord with a preset schedule) it is stored in an event buffer along with its occurrence time. The subjects response to the event (i.e., key presses) is also stored with its time tag. A summary printout of events is given upon termination of the experiment.

(2) Control Processing. In this series of experiments the objective is to measure the subjects ability to match letters or words in a given limited decision time. The experiment is administered at 2 levels of difficulty (i.e., induced cognitive load).

(1) Matching letters (easy).
(2) Matching antonyms (difficult).

From a predefined table of words and letters stored in memory the subject is presented with pairwise letters or words and given two seconds to respond. He is expected to respond by pushing either one of two buttons labled TRUE or FALSE.

The system records the correct response to the event (TRUE, FALSE) as well as the subject's actual response.

Performance Evaluation. Each event associated with the display of a letter pair or word pair is stored in terms of its value and associated occurrence time in the buffer. The event associated with the subject's response is also stored along with its time of occurrence.

The summary printout consists of messages such as EVENT=TRUE or FALSE along with the corresponding time of occurrence with, followed by: RESPONSE=TRUE or FALSE corresponding to the subject's response along with the time of that response. Lack of correspondence between stimulus events and subject's responses are flagged by error messages of the type: ERROR IN RESPONSE X.

(3) Motor Response Experiment. The experiment measures the subject's motor response ability using a deflected object on the screen which is controllable via a joystick interface to the Apple.

A graphic representation of a horizontal bar with a moving block initially at its center is displayed on the screen. The block is continuously deflected in accord with:

$$y(t)_{new} = y(t) + \lambda\,(y(t)+k\;x(t))$$

where

$y_{new}(t)$ = new position of block on scale
$y(t)$ = new old position of block on scale
$x(t)$ = joystick deflection from center
λ = level of difficulty
k = constant

The net effect is that the block is always being forced off-center to either end of the bar. The software continuously reads the joystick inputs to the system and incorporates the latest values in computing the new position of the block. this experiment tests the subject's ability to keep the block centered with the help of a joystick control.

The 2 levels of difficulty which are used in the experiment are incorporated in calculating the new position of the block. The higher the level of difficulty, the harder it is to control the block. Throughout the experiment, the following information is collected:

- o Value of off-center distance
- o Edge collisions

For a successful control trial (i.e., no edge collisions), the last 100 sample values of the distance of the block from the bar's center is stored in the memory buffer. Then the RMS distance values are calculated. For a trial in which edge collision(s) have occurred, the elapsed time and the accumulated RMS distance value for the particular control attempt was recorded. At the end of the trial, the time duration and the average RMS values across the control attempts were calculated and printed out in a summary report. A listing of the FORTH "words" used is given in Table A-2.

TABLE A-2

FORTH "Words" AND ASSOCIATED FUNCTIONS

initialize clock	- Initializes the real time clock on Apple 2e
initialize comms	- Initializes the serial communications card on 2e
clear buffer	- Clears the internal buffer
comm	- Initiates communications between 2e and 68000
decode start	- Receives initial starting messages from 68000
decode run	- Decodes interrupts from 68000 key board during experiment
start exp 0	- Sets initial conditions variables to start the perceptual experiment
start exp 1	- Sets initial conditions variables to start the central experiment
start exp 2	- Sets initial conditions variables to start the motor response experiment
maintain exp 0	- Monitors events in perceptual experiment
maintain exp 1	- Monitors events in central experiment
maintain exp 2	- Monitors events in motor response experiment
zero event tab	- Event table for perceptual experiment
zero mean tab	- Table of means for perceptual experiment
set seed	- Sets up a random number generator
board	- Draws graphic scale for motor response experiment
narrow	- Draws graphic displays for perceptual experiment
get - key	- Reads subject response to various experiments
arrowmean	- Subroutine to oscillate arrow in perceptual experiment
good/bad	- Determines if events in central experiment are true or false
net dot	- Calculates continuous new positions for block in motor experiment

TABLE A-2 (Cont'd)

edge test	- Checks for edge collision in motor response experiment
get RMS	- Calculates the RMS values in motor response
store events	- Stores all events (key strokes, etc) in internal buffer
ptime	- Reads clock and stores event time
printen	- Prints contents of buffer in a readable format
stick pos	- Reads joystick values
draw dot	- draws graphic for motor response experiment

APPENDIX B

EXPERIMENTAL SUBJECTS' INSTRUCTIONS

Appendix B

Experimental Subjects' Instructions

This experiment is part of a Program of continuing research at Perceptronics in human (Pilot) performance and decision making. The purpose of this particular experiment is to analyze ways in which human operators' myoelectric (muscle) signals respond and how a computer might help to determine an operator's mental state via these signals. You are an integral part of this research since your performance provides the baseline data for predicting operator performance, and estimating the effectiveness of computer-based analysis techniques.

Tasks Overview

There are two types of tasks that you will be asked to perform in the experiment. They are: (1) central processing (or linguistic processing) task and (2) motor (or control) tracking task. Within each task, there are two difficulty levels -- low and high. You will be given direction as to the specific type and difficulty level of the task and the approximate time it will take to complete. Please concentrate on the task, as your response and performance will be closely monitored and scored, based on both your response time and response accuracy. (We will have a bonus for the best performer after we have completed the experiment.) At the end of each run, you will be given a questionnaire to fill out. Information on these questionnaires will not be used to rate your score, so please use your unbiased judgment to answer those questions.

The following paragraphs describe the two types of tasks.

<u>Central Processing (Linguistic Processing) Task</u>. In this task, you will see a sequence of letter pairs or word pairs shown on the screen every two to three seconds. You will be asked to compare and classify them as "same" (true event) or "different" (false event) based on: (1) the character categories (e.g., aa, cc are the same pairs: ae, ac are different pairs). Upper and lower case representations of the same letter (e.g., Aa are classified as different); (2) rhymes ('go' and 'throw' are true events, 'go' and 'soon' are false events); (3) antonym categories (true event, if the two words are antonyms [i.e., opposites] and false event, if otherwise). Please respond as soon as you can and, at the same time, avoid making any mistakes. A decision needs to be made before the next pair appears so that you don't miss any response opportunities. Missed events and incorrect responses will be registered as errors.

<u>Motor (Control) Tracking Task</u>. In this task, you will see a cursor which moves on a horizontal axis. You will be asked to use a joystick to maintain the cursor as close to the center as possible. A tone will be given when the cursor moves off the scale and the cursor will start from the center again. Performance will be measured as: (1) the average time until loss of control, and (2) the closeness of the cursor to the center of the axis over the entire trial.

APPENDIX C

SAMPLE PRINTOUT

Apr 29 12:42 1984 Data.Sample Page 1

EMG ANALYSIS PROGRAM

FILE IS ps2.data
Robert 4/16/84 14:30

NO. OF RECORDS =   3 NO. OF SAMPLES = 500

RECORD =   1

DATA:

-47	-36	-50	-49	-27	-35	-37	-41	-51	-37
-31	-37	-40	-27	-41	-40	-26	-26	-21	-23
-12	-8	-23	-28	-23	-29	-31	-42	-51	-48
-58	-57	-56	-52	-29	-14	27	26	36	51
53	56	41	2	-17	-48	-44	-44	-42	-31
-44	-56	-33	-60	-41	-46	-46	-36	-42	-39
-46	-44	-41	-51	-43	-44	-41	-44	-47	-50
-48	-48	-42	-49	-34	-42	-41	-41	-46	-35
-49	-34	-54	-57	-52	-48	-39	-40	-52	-54
-49	-59	-44	-51	-39	-37	-45	-37	-49	-29
-36	-46	-23	-20	-27	-33	-31	-18	-27	-19
-34	-42	-33	-64	-69	-66	-64	-49	-52	-36
-14	6	37	21	37	48	55	38	-5	-33
-45	-47	-30	-46	-33	-35	-58	-33	-49	-39
-48	-47	-33	-48	-50	-38	-52	-46	-42	-55
-31	-60	-49	-43	-61	-47	-47	-36	-36	-41
-36	-42	-45	-42	-51	-47	-53	-44	-50	-51
-40	-37	-31	-48	-41	-41	-32	-31	-45	-43
-36	-50	-33	-38	-34	-41	-28	-27	-43	-33
-24	-38	-19	-26	-25	-42	-35	-39	-51	-53
-59	-65	-57	-52	-29	-14	9	37	31	49
56	56	41	-5	-32	-36	-48	-42	-56	-49
-40	-49	-42	-45	-30	-47	-44	-37	-51	-37
-48	-49	-47	-52	-50	-40	-46	-38	-47	-52
-25	-58	-45	-49	-52	-36	-44	-50	-33	-32
-50	-46	-43	-45	-38	-32	-46	-38	-48	-46
-39	-46	-39	-37	-35	-27	-45	-38	-51	-44
-25	-38	-29	-21	-24	-20	-35	-34	-27	-31
-30	-43	-46	-51	-57	-63	-60	-60	-38	-35
-7	7	27	52	44	55	59	22	0	-43
-43	-51	-40	-46	-58	-43	-55	-37	-35	-45
-44	-41	-46	-38	-47	-36	-43	-46	-32	-52
-42	-48	-43	-36	-50	-43	-39	-52	-53	-50
-49	-36	-44	-36	-50	-42	-32	-45	-33	-49
-51	-45	-49	-50	-51	-47	-52	-42	-51	-57
-44	-41	-36	-22	-45	-38	-39	-17	-27	-34
-29	-20	-20	-28	-37	-38	-39	-55	-40	-63
-72	-71	-69	-37	-39	0	13	29	48	37
51	56	26	16	-30	-49	-35	-45	-50	-38
-45	-30	-49	-52	-56	-45	-45	-39	-34	-45
-42	-56	-44	-42	-41	-42	-35	-50	-44	-49
-43	-49	-44	-39	-49	-45	-39	-55	-34	-31
-43	-40	-36	-42	-44	-51	-35	-43	-43	-42

-39	-48	-51	-41	-39	-44	-34	-47	-30	-41
-40	-33	-35	-18	-31	-36	-26	-38	-23	-29
-23	-42	-50	-40	-54	-62	-58	-60	-26	-18
17	12	37	49	56	64	51	33	7	-37
-53	-42	-46	-45	-47	-49	-39	-58	-50	-47
-40	-49	-31	-49	-51	-41	-39	-55	-39	-51
-57	-50	-73	-60	-64	-76	-61	-73	-60	-81

UNIVARIATE STOCHASTIC MODEL IDENTIFICATION

TIME SERIES:

-47	-36	-50	-49	-27	-35	-37	-41	-51	-37
-31	-37	-40	-27	-41	-40	-26	-26	-21	-23
-12	-8	-23	-28	-23	-29	-31	-42	-51	-48
-58	-57	-56	-52	-29	-14	27	26	36	51
53	56	41	2	-17	-48	-44	-44	-42	-31
-44	-56	-33	-60	-41	-46	-46	-36	-42	-39
-46	-44	-41	-51	-43	-44	-41	-44	-47	-50
-48	-48	-42	-49	-34	-42	-41	-41	-46	-35
-49	-34	-54	-57	-52	-48	-39	-40	-52	-54
-49	-59	-44	-51	-39	-37	-45	-37	-49	-29
-36	-46	-23	-20	-27	-33	-31	-18	-27	-19
-34	-42	-33	-64	-69	-66	-64	-49	-52	-36
-14	6	37	21	37	48	55	38	-5	-33
-45	-47	-30	-46	-33	-35	-58	-33	-49	-39
-48	-47	-33	-48	-50	-38	-52	-46	-42	-55
-31	-60	-49	-43	-61	-47	-47	-36	-36	-41
-36	-42	-45	-42	-51	-47	-53	-44	-50	-51
-40	-37	-31	-48	-41	-41	-32	-31	-45	-43
-36	-50	-33	-38	-34	-41	-28	-27	-43	-33
-24	-38	-19	-26	-25	-42	-35	-39	-51	-53
-59	-65	-57	-52	-29	-14	9	37	31	49
56	56	41	-5	-32	-36	-48	-42	-56	-49
-40	-49	-42	-45	-30	-47	-44	-37	-51	-37
-48	-49	-47	-52	-50	-40	-46	-38	-47	-52
-25	-58	-45	-49	-52	-36	-44	-50	-33	-32
-50	-46	-43	-45	-38	-32	-46	-38	-48	-46
-39	-46	-39	-37	-35	-27	-45	-38	-51	-44
-25	-38	-29	-21	-24	-20	-35	-34	-27	-31
-30	-43	-46	-51	-57	-63	-60	-60	-38	-35
-7	7	27	52	44	55	59	22	0	-43
-43	-51	-40	-46	-58	-43	-55	-37	-35	-45
-44	-41	-46	-38	-47	-36	-43	-46	-32	-52
-42	-48	-43	-36	-50	-43	-39	-52	-53	-50
-49	-36	-44	-36	-50	-42	-32	-45	-33	-49
-51	-45	-49	-50	-51	-47	-52	-42	-51	-57
-44	-41	-36	-22	-45	-38	-39	-17	-27	-34
-29	-20	-20	-28	-37	-38	-39	-55	-40	-63
-72	-71	-69	-37	-39	0	13	29	48	37
51	56	26	16	-30	-49	-35	-45	-50	-38
-45	-30	-49	-52	-56	-45	-45	-39	-34	-45

-42	-56	-44	-42	-41	-42	-35	-50	-44	-49
-43	-49	-44	-39	-49	-45	-39	-55	-34	-31
-43	-40	-36	-42	-44	-51	-35	-43	-43	-42
-39	-48	-51	-41	-39	-44	-34	-47	-30	-41
-40	-33	-35	-18	-31	-36	-26	-38	-23	-29
-23	-42	-50	-40	-54	-62	-58	-60	-26	-18
17	12	37	49	56	64	51	33	7	-37
-53	-42	-46	-45	-47	-49	-39	-58	-50	-47
-40	-49	-31	-49	-51	-41	-39	-55	-39	-51
-57	-50	-73	-60	-64	-76	-61	-73	-60	-81

NUMBER OF OBSERVATIONS =   500

MAXIMUM LAG OF ACVF, ACF = 20

MAXIMUM LAG OF PACF = 20

LEVEL OF DIFFERENCING =   0

DIFFERENCED AND TRANSFORMED SERIES:

-13	-2	-16	-15	7	-1	-3	-7	-17	-3
3	-3	-6	7	-7	-6	8	8	13	11
22	26	11	6	11	5	3	-8	-17	-14
-24	-23	-22	-18	5	20	61	60	70	85
87	90	75	36	17	-14	-10	-10	-8	3
-10	-22	1	-26	-7	-12	-12	-2	-8	-5
-12	-10	-7	-17	-9	-10	-7	-10	-13	-16
-14	-14	-8	-15	0	-8	-7	-7	-12	-1
-15	0	-20	-23	-18	-14	-5	-6	-18	-20
-15	-25	-10	-17	-5	-3	-11	-3	-15	5
-2	-12	11	14	7	1	3	16	7	15
0	-8	1	-30	-35	-32	-30	-15	-18	-2
20	40	71	55	71	82	89	72	29	1
-11	-13	4	-12	1	-1	-24	1	-15	-5
-14	-13	1	-14	-16	-4	-18	-12	-8	-21
3	-26	-15	-9	-27	-13	-13	-2	-2	-7
-2	-8	-11	-8	-17	-13	-19	-10	-16	-17
-6	-3	3	-14	-7	-7	2	3	-11	-9
-2	-16	1	-4	0	-7	6	7	-9	1
10	-4	15	8	9	-8	-1	-5	-17	-19
-25	-31	-23	-18	5	20	43	71	65	83
90	90	75	29	2	-2	-14	-8	-22	-15
-6	-15	-8	-11	4	-13	-10	-3	-17	-3
-14	-15	-13	-18	-16	-6	-12	-4	-13	-18
9	-24	-11	-15	-18	-2	-10	-16	1	2
-16	-12	-9	-11	-4	2	-12	-4	-14	-12
-5	-12	-5	-3	-1	7	-11	-4	-17	-10
9	-4	5	13	10	14	-1	0	7	3
4	-9	-12	-17	-23	-29	-26	-26	-4	-1
27	41	61	86	78	89	93	56	34	-9
-9	-17	-6	-12	-24	-9	-21	-3	-1	-11
-10	-7	-12	-4	-13	-2	-9	-12	2	-18
-8	-14	-9	-2	-16	-9	-5	-18	-19	-16
-15	-2	-10	-2	-16	-8	2	-11	1	-15

-17	-11	-15	-16	-17	-13	-18	-8	-17	-23
-10	-7	-2	12	-11	-4	-5	17	7	0
5	14	14	6	-3	-4	-5	-21	-6	-29
-38	-37	-35	-3	-5	34	47	63	82	71
85	90	60	50	4	-15	-1	-11	-16	-4
-11	4	-15	-18	-22	-11	-11	-5	0	-11
-8	-22	-10	-8	-7	-8	-1	-16	-10	-15
-9	-15	-10	-5	-15	-11	-5	-21	0	3
-9	-6	-2	-8	-10	-17	-1	-9	-9	-8
-5	-14	-17	-7	-5	-10	0	-13	4	-7
-6	1	-1	16	3	-2	8	-4	11	5
11	-8	-16	-6	-20	-28	-24	-26	8	16
51	46	71	83	90	98	85	67	41	-3
-19	-8	-12	-11	-13	-15	-5	-24	-16	-13
-6	-15	3	-15	-17	-7	-5	-21	-5	-17
-23	-16	-39	-26	-30	-42	-27	-39	-26	-47

NUMBER OF DIFFERENCED VALUES =   500

AUTOCOVARIANCES:

6.618940e+02	5.766620e+02	5.067000e+02	3.962780e+02	2.628940e+02
1.607760e+02	3.327000e+01	-5.451800e+01	-1.173140e+02	-1.652680e+02
-1.618740e+02	-1.611400e+02	-1.262180e+02	-8.240400e+01	-4.988200e+01
4.100000e-01	1.761200e+01	3.443400e+01	4.930400e+01	3.698800e+01
4.790600e+01				

AUTOCORRELATIONS:

1.000000e+00	8.712301e-01	7.655304e-01	5.987031e-01	3.971844e-01
2.429029e-01	5.026484e-02	-8.236666e-02	-1.772399e-01	-2.496895e-01
-2.445618e-01	-2.434529e-01	-1.906922e-01	-1.244973e-01	-7.536252e-02
6.194345e-04	2.660849e-02	5.202343e-02	7.448927e-02	5.588206e-02
7.237715e-02				

STANDARD ERRORS OF AUTOCORRELATIONS:

0.000000e+00	7.096595e-02	8.590875e-02	9.388340e-02	9.718598e-02
9.839269e-02	9.844404e-02	9.858177e-02	9.921704e-02	1.004659e-01
1.016496e-01	1.028091e-01	1.035141e-01	1.038131e-01	1.039225e-01
1.039225e-01	1.039361e-01	1.039882e-01	1.040948e-01	1.041548e-01
1.042554e-01				

PARTIAL AUTOCORRELATIONS:

8.712301e-01	2.692793e-02	-3.062949e-01	-3.110078e-01	8.840510e-02
-1.811273e-01	1.199930e-02	8.347133e-02	-1.612088e-03	9.745529e-02
-4.618127e-02	4.914805e-02	1.381621e-02	-6.271049e-02	2.364367e-02
-8.022220e-02	-2.601486e-02	7.078087e-02	-2.924550e-02	9.288832e-02

STANDARD ERROR OF PARTIAL AUTOCORRELATIONS = 4.472136e-02

EMG ANALYSIS PROGRAM

FILE IS os2.data
Robert 4/16/84 14:30

NO. OF RECORDS = 3 NO. OF SAMPLES = 500

RECORD = 1

DATA:

-47	-36	-50	-49	-27	-35	-37	-41	-51	-37
-31	-37	-40	-27	-41	-40	-26	-26	-21	-23
-12	-8	-23	-28	-23	-29	-31	-42	-51	-48
-58	-57	-56	-52	-29	-14	27	26	36	51
53	56	41	2	-17	-48	-44	-44	-42	-31
-44	-56	-33	-60	-41	-46	-46	-36	-42	-39
-46	-44	-41	-51	-43	-44	-41	-44	-47	-50
-48	-48	-42	-49	-34	-42	-41	-41	-46	-35
-49	-34	-54	-57	-52	-48	-39	-40	-52	-54
-49	-59	-44	-51	-39	-37	-45	-37	-49	-29
-36	-46	-23	-20	-27	-33	-31	-18	-27	-19
-34	-42	-33	-64	-69	-66	-64	-49	-52	-36
-14	6	37	21	37	48	55	38	-5	-33
-45	-47	-30	-46	-33	-35	-58	-33	-49	-39
-48	-47	-33	-48	-50	-38	-52	-46	-42	-55
-31	-60	-49	-43	-61	-47	-47	-36	-36	-41
-36	-42	-45	-42	-51	-47	-53	-44	-50	-51
-40	-37	-31	-48	-41	-41	-32	-31	-45	-43
-36	-50	-33	-38	-34	-41	-28	-27	-43	-33
-24	-38	-19	-26	-25	-42	-35	-39	-51	-53
-59	-65	-57	-52	-29	-14	9	37	31	49
56	56	41	-5	-32	-36	-48	-42	-56	-49
-40	-49	-42	-45	-30	-47	-44	-37	-51	-37
-48	-49	-47	-52	-50	-40	-46	-38	-47	-52
-25	-58	-45	-49	-52	-36	-44	-50	-33	-32
-50	-46	-43	-45	-38	-32	-46	-38	-48	-46
-39	-46	-39	-37	-35	-27	-45	-38	-51	-44
-25	-38	-29	-21	-24	-20	-35	-34	-27	-31
-30	-43	-46	-51	-57	-63	-60	-60	-38	-35
-7	7	27	52	44	55	59	22	0	-43
-43	-51	-40	-46	-58	-43	-55	-37	-35	-45
-44	-41	-46	-38	-47	-36	-43	-46	-32	-52
-42	-48	-43	-36	-50	-43	-39	-52	-53	-50
-49	-36	-44	-36	-50	-42	-32	-45	-33	-49
-51	-45	-49	-50	-51	-47	-52	-42	-51	-57
-44	-41	-36	-22	-45	-38	-39	-17	-27	-34
-29	-20	-20	-28	-37	-38	-39	-55	-40	-63
-72	-71	-69	-37	-39	0	13	29	48	37
51	56	26	16	-30	-49	-35	-45	-50	-38
-45	-30	-49	-52	-56	-45	-45	-39	-34	-45
-42	-56	-44	-42	-41	-42	-35	-50	-44	-49
-43	-49	-44	-39	-49	-45	-39	-55	-34	-31
-43	-40	-36	-42	-44	-51	-35	-43	-43	-42

-39	-48	-51	-41	-39	-44	-34	-47	-30	-41
-40	-33	-35	-18	-31	-36	-26	-38	-23	-29
-23	-42	-50	-40	-54	-62	-58	-60	-26	-18
17	12	37	49	56	64	51	33	7	-37
-53	-42	-46	-45	-47	-49	-39	-58	-50	-47
-40	-49	-31	-49	-51	-41	-39	-55	-39	-51
-57	-50	-73	-60	-64	-76	-61	-73	-60	-81

UNIVARIATE STOCHASTIC MODEL PRELIMINARY ESTIMATION

TIME SERIES:

-47	-36	-50	-49	-27	-35	-37	-41	-51	-37
-31	-37	-40	-27	-41	-40	-26	-26	-21	-23
-12	-8	-23	-28	-23	-29	-31	-42	-51	-48
-58	-57	-56	-52	-29	-14	27	26	36	51
53	56	41	2	-17	-48	-44	-44	-42	-31
-44	-56	-33	-60	-41	-46	-46	-36	-42	-39
-46	-44	-41	-51	-43	-44	-41	-44	-47	-50
-48	-48	-42	-49	-34	-42	-41	-41	-46	-35
-49	-34	-54	-57	-52	-48	-39	-40	-52	-54
-49	-59	-44	-51	-39	-37	-45	-37	-49	-29
-36	-46	-23	-20	-27	-33	-31	-18	-27	-19
-34	-42	-33	-64	-69	-66	-64	-49	-52	-36
-14	6	37	21	37	48	55	38	-5	-33
-45	-47	-30	-46	-33	-35	-58	-33	-49	-39
-48	-47	-33	-48	-50	-38	-52	-46	-42	-55
-31	-60	-49	-43	-61	-47	-47	-36	-36	-41
-36	-42	-45	-42	-51	-47	-53	-44	-50	-51
-40	-37	-31	-48	-41	-41	-32	-31	-45	-43
-36	-50	-33	-38	-34	-41	-28	-27	-43	-33
-24	-38	-19	-26	-25	-42	-35	-39	-51	-53
-59	-65	-57	-52	-29	-14	9	37	31	49
56	56	41	-5	-32	-36	-48	-42	-56	-49
-40	-49	-42	-45	-30	-47	-44	-37	-51	-37
-48	-49	-47	-52	-50	-40	-46	-38	-47	-52
-25	-58	-45	-49	-52	-36	-44	-50	-33	-32
-50	-46	-43	-45	-38	-32	-46	-38	-48	-46
-39	-46	-39	-37	-35	-27	-45	-38	-51	-44
-25	-38	-29	-21	-24	-20	-35	-34	-27	-31
-30	-43	-46	-51	-57	-63	-60	-60	-38	-35
-7	7	27	52	44	55	59	22	0	-43
-43	-51	-40	-46	-58	-43	-55	-37	-35	-45
-44	-41	-46	-38	-47	-36	-43	-46	-32	-52
-42	-48	-43	-36	-50	-43	-39	-52	-53	-50
-49	-36	-44	-36	-50	-42	-32	-45	-33	-49
-51	-45	-49	-50	-51	-47	-52	-42	-51	-57
-44	-41	-36	-22	-45	-38	-39	-17	-27	-34
-29	-20	-20	-28	-37	-38	-39	-55	-40	-63
-72	-71	-69	-37	-39	0	13	29	48	37
51	56	26	16	-30	-49	-35	-45	-50	-38
-45	-30	-49	-52	-56	-45	-45	-39	-34	-45

-42	-56	-44	-42	-41	-42	-35	-50	-44	-49
-43	-49	-44	-39	-49	-45	-39	-55	-34	-31
-43	-40	-36	-42	-44	-51	-35	-43	-43	-42
-39	-48	-51	-41	-39	-44	-34	-47	-30	-41
-40	-33	-35	-18	-31	-36	-26	-38	-23	-29
-23	-42	-50	-40	-54	-62	-58	-60	-26	-18
17	12	37	49	56	64	51	33	7	-37
-53	-42	-46	-45	-47	-49	-39	-58	-50	-47
-40	-49	-31	-49	-51	-41	-39	-55	-39	-51
-57	-50	-73	-60	-64	-76	-61	-73	-60	-81

NUMBER OF DIFFERENCINGS = 0

NUMBER OF AUTOREGRESSIVE PARAMETERS = 6

NUMBER OF MOVING AVERAGE PARAMETERS = 0

DIFFERENCED AND TRANSFORMED SERIES:

-13	-2	-16	-15	7	-1	-3	-7	-17	-3
3	-3	-6	7	-7	-6	8	8	13	11
22	26	11	6	11	5	3	-8	-17	-14
-24	-23	-22	-18	5	20	61	60	70	85
87	90	75	36	17	-14	-10	-10	-8	3
-10	-22	1	-26	-7	-12	-12	-2	-8	-5
-12	-10	-7	-17	-9	-10	-7	-10	-13	-16
-14	-14	-8	-15	0	-8	-7	-7	-12	-1
-15	0	-20	-23	-18	-14	-5	-6	-18	-20
-15	-25	-10	-17	-5	-3	-11	-3	-15	5
-2	-12	11	14	7	1	3	16	7	15
0	-8	1	-30	-35	-32	-30	-15	-18	-2
20	40	71	55	71	82	89	72	29	1
-11	-13	4	-12	1	-1	-24	1	-15	-5
-14	-13	1	-14	-16	-4	-18	-12	-8	-21
3	-26	-15	-9	-27	-13	-13	-2	-2	-7
-2	-8	-11	-8	-17	-13	-19	-10	-16	-17
-6	-3	3	-14	-7	-7	2	3	-11	-9
-2	-16	1	-4	0	-7	6	7	-9	1
10	-4	15	8	9	-8	-1	-5	-17	-19
-25	-31	-23	-18	5	20	43	71	65	83
90	90	75	29	2	-2	-14	-8	-22	-15
-6	-15	-8	-11	4	-13	-10	-3	-17	-3
-14	-15	-13	-18	-16	-6	-12	-4	-13	-18
9	-24	-11	-15	-18	-2	-10	-16	1	2
-16	-12	-9	-11	-4	2	-12	-4	-14	-12
-5	-12	-5	-3	-1	7	-11	-4	-17	-10
9	-4	5	13	10	14	-1	0	7	3
4	-9	-12	-17	-23	-29	-26	-26	-4	-1
27	41	61	86	78	89	93	56	34	-9
-9	-17	-6	-12	-24	-9	-21	-3	-1	-11
-10	-7	-12	-4	-13	-2	-9	-12	2	-18
-8	-14	-9	-2	-16	-9	-5	-18	-19	-16
-15	-2	-10	-2	-16	-8	2	-11	1	-15
-17	-11	-15	-16	-17	-13	-18	-8	-17	-23
-10	-7	-2	12	-11	-4	-5	17	7	0
5	14	14	6	-3	-4	-5	-21	-6	-29

-38	-37	-35	-3	-5	34	47	63	82	71
85	90	60	50	4	-15	-1	-11	-16	-4
-11	4	-15	-18	-22	-11	-11	-5	0	-11
-8	-22	-10	-8	-7	-8	-1	-16	-10	-15
-9	-15	-10	-5	-15	-11	-5	-21	0	3
-9	-6	-2	-8	-10	-17	-1	-9	-9	-8
-5	-14	-17	-7	-5	-10	0	-13	4	-7
-6	1	-1	16	3	-2	8	-4	11	5
11	-8	-16	-6	-20	-28	-24	-26	8	16
51	46	71	83	90	98	85	67	41	-3
-19	-8	-12	-11	-13	-15	-5	-24	-16	-13
-6	-15	3	-15	-17	-7	-5	-21	-5	-17
-23	-16	-39	-26	-30	-42	-27	-39	-26	-47

AUTOCOVARIANCES:

6.618940e+02 5.766620e+02 5.067000e+02 3.962780e+02 2.628940e+02
1.607760e+02 3.327000e+01

INITIAL ESTIMATES OF AUTOREGRESSIVE PARAMETERS:

8.042637e-01 3.107581e-01 -8.655653e-02 -3.095668e-01 2.311791e-01
-1.811271e-01

INITIAL ESTIMATES OF MOVING AVERAGE PARAMETERS:

INITIAL ESTIMATE OF WHITE NOISE VARIANCE = 1.251865e+02

UNIVARIATE STOCHASTIC MODEL ESTIMATION

```
h[1] =  1.120436e-02 phi2[1] =  8.154680e-01
h[2] = -4.626880e-03 phi2[2] =  3.061312e-01
h[3] = -8.433133e-04 phi2[3] = -8.739984e-02
h[4] = -7.891212e-03 phi2[4] = -3.174580e-01
h[5] =  1.182190e-02 phi2[5] =  2.430010e-01
h[6] = -4.118866e-03 phi2[6] = -1.852460e-01

S(B0) =  5.994822e+04 S(B) =  5.990726e+04

h[1] =  6.477033e-03 phi2[1] =  8.219450e-01
h[2] = -5.424129e-03 phi2[2] =  3.007071e-01
h[3] = -1.283012e-03 phi2[3] = -8.868285e-02
h[4] = -5.048565e-03 phi2[4] = -3.225065e-01
h[5] =  1.012739e-02 phi2[5] =  2.531284e-01
h[6] = -3.846748e-03 phi2[6] = -1.890927e-01

S(B0) =  5.990726e+04 S(B) =  5.989479e+04

h[1] =  3.048000e-03 phi2[1] =  8.249929e-01
h[2] = -3.067821e-03 phi2[2] =  2.976393e-01
h[3] = -6.991340e-04 phi2[3] = -8.938198e-02
h[4] = -1.771282e-03 phi2[4] = -3.242778e-01
h[5] =  5.258203e-03 phi2[5] =  2.583866e-01
h[6] = -2.474323e-03 phi2[6] = -1.915670e-01
```

S(B0) = 5.989479e+04 S(B) = 5.989257e+04

h[1] = 8.952189e-04 phi2[1] = 8.258881e-01
h[2] = -9.962639e-04 phi2[2] = 2.966430e-01
h[3] = -2.281227e-04 phi2[3] = -8.961010e-02
h[4] = -3.307642e-04 phi2[4] = -3.246086e-01
h[5] = 1.568982e-03 phi2[5] = 2.599556e-01
h[6] = -8.572481e-04 phi2[6] = -1.924243e-01

S(B0) = 5.989257e+04 S(B) = 5.989244e+04

h[1] = 1.178491e-04 phi2[1] = 8.260059e-01
h[2] = -1.658523e-04 phi2[2] = 2.964771e-01
h[3] = 1.457869e-06 phi2[3] = -8.960864e-02
h[4] = -3.272739e-05 phi2[4] = -3.246413e-01
h[5] = 2.015861e-04 phi2[5] = 2.601571e-01
h[6] = -1.188248e-04 phi2[6] = -1.925431e-01

S(B0) = 5.989244e+04 S(B) = 5.989241e+04

FINAL AUTOREGRESSIVE PARAMETERS:

8.258881e-01 2.966430e-01 -8.961010e-02 -3.246086e-01 2.599556e-01
-1.924243e-01

FINAL MOVING AVERAGE PARAMETERS:

FINAL RESIDUALS:

0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
0.000000e+00	-1.277010e+01	-4.693109e+00	-7.325656e+00	7.817104e+00
1.052642e+01	-7.795923e+00	-8.957023e+00	1.521253e+01	-1.278771e+01
-5.163909e+00	1.506859e+01	5.800202e+00	-1.764403e+00	-1.738007e-01
1.258538e+01	5.094998e+00	-1.233386e+01	-7.095396e+00	1.189485e+01
-4.144789e-02	-2.809669e+00	-6.883995e+00	-6.707145e+00	2.600148e+00
-6.320801e+00	-2.963669e+00	-1.112595e-03	3.177014e+00	1.690865e+01
1.531770e+01	3.560544e+01	-4.136733e-01	6.212603e+00	1.658422e+01
1.697524e+01	6.673498e+00	1.342141e+00	-2.390309e+01	-7.300859e+00
-9.043783e+00	1.743602e+01	1.344268e+01	1.256253e+01	9.640941e+00
-7.336115e+00	-1.868840e+01	2.048324e+01	-2.006661e+01	6.639677e+00
-2.381016e+00	1.776683e+00	-2.090010e+00	8.151793e-01	-5.953575e+00
-7.799441e+00	8.381496e-01	-1.550263e-02	-9.255919e+00	2.085577e+00
7.599121e-01	4.235004e-01	-7.681743e+00	-3.409921e+00	-7.101993e+00
7.699441e-01	-2.206850e+00	3.314347e+00	-9.232991e+00	1.062018e+01
-8.251165e+00	-3.388477e+00	-4.329063e+00	-2.499223e+00	4.876654e+00
-1.143428e+01	9.617676e+00	-1.906255e+01	-6.378500e+00	1.002103e-02
9.603479e+00	4.624388e-01	-1.597426e+00	-1.652846e+01	-8.093284e+00
4.872372e+00	-1.163361e+01	8.059300e+00	-5.636712e+00	6.632618e+00
-2.788096e+00	-8.196051e+00	-1.202749e+00	-8.656132e+00	1.434727e+01
-5.701574e+00	-1.186718e+01	1.574606e+01	1.324083e+01	-1.373618e+01
-1.036178e+01	7.657464e+00	1.322888e+01	-6.264978e+00	5.940184e+00
-1.097022e+01	-7.216078e+00	7.641499e+00	-2.232451e+01	-1.378924e+01
6.184477e+00	6.526872e+00	4.595255e+00	-2.950121e+00	7.565567e+00
1.749267e+01	1.923450e+01	2.413604e+01	-1.256795e+01	1.164735e+01
2.080928e+01	2.164155e+01	-1.237285e+01	-2.710535e+01	-1.758935e+01

7.259324e+00	1.440138e+01	2.591183e+01	-5.79[illegible]459e+00	1.030881e+01
9.242917e-01	-2.198488e+01	1.377092e+01	-4.582294e+00	2.047380e+00
-1.266953e+01	5.072614e+00	5.694227e+00	-9.755354e+00	-1.203024e+01
1.191416e+01	-1.019461e+01	-4.687194e+00	5.529854e+00	-1.227924e+01
1.375955e+01	-2.295084e+01	7.603100e-01	4.323641e+00	-1.255372e+01
-2.635986e+00	7.406402e+00	6.148254e+00	-6.967991e+00	-4.852798e+00
-1.840662e+00	-4.222253e+00	-7.057701e+00	1.141495e+00	-7.061078e+00
-9.963971e-01	-5.813303e+00	6.748107e+00	-8.825201e+00	-3.862013e+00
5.830930e+00	4.756051e+00	-5.160924e-01	-1.940869e+01	2.796479e+00
5.177436e-01	9.202321e+00	-3.104205e+00	-1.275383e+01	-3.772450e+00
1.008683e+01	-1.355720e+01	1.003529e+01	2.564862e-01	1.146864e+00
-1.212946e+01	1.552182e+01	-5.160060e-01	-1.595609e+01	3.852194e+00
1.623851e+01	-1.399646e+01	1.184011e+01	1.705530e+00	-1.160878e+00
-2.016755e+01	1.148739e+01	-3.066639e+00	-9.562599e+00	-6.963371e+00
-1.226391e+00	-9.142433e+00	3.905020e+00	5.240665e+00	1.746358e+01
1.192906e+01	1.916805e+01	2.417287e+01	-2.725015e+00	1.383761e+01
1.825299e+01	1.259096e+01	-7.673199e+00	-2.786703e+01	-1.598803e+01
1.625632e+01	7.925008e+00	1.157010e+01	-3.876786e+00	8.699315e+00
8.557823e+00	-6.908787e+00	-2.931656e+00	-1.170411e+00	1.183211e+01
-1.995311e+01	-1.287818e+00	5.096264e+00	-1.010228e+01	3.657524e+00
-5.845200e+00	-4.946794e+00	-3.390229e+00	-1.200205e+00	-5.657672e+00
9.581826e+00	-6.925882e+00	9.068572e-01	-9.690443e+00	-8.404202e+00
2.194954e+01	-2.659186e+01	-9.506350e-01	-1.222538e+00	5.999141e-01
2.736074e+00	4.725583e-02	-1.538861e+01	1.[illegible]94113e+01	6.167916e+00
-2.557199e+01	-2.268496e+00	8.395819e+00	-4.130579e+00	1.158010e+00
8.408967e+00	-1.633171e+01	1.418745e+00	-7.128252e+00	-7.539434e-01
3.520306e+00	-3.359504e+00	-4.952386e-01	3.215483e+00	6.880418e-01
3.363150e+00	-1.621910e+01	9.355188e-01	-1.031297e+01	6.195900e+00
1.636056e+01	-7.081887e+00	-1.857526e+00	1.126708e+01	-3.283800e-01
-3.229466e+00	-9.969246e+00	-2.805756e-01	9.379967e+00	1.575653e+00
-2.593909e+00	-9.612313e+00	-3.404912e+00	-4.906978e+00	-4.341139e+00
-9.420988e+00	2.464165e+00	-2.115993e+00	1.723126e+01	9.805229e-01
2.135572e+01	1.137794e+01	1.949699e+01	2.159011e+01	8.071075e-01
1.063337e+01	1.840267e+01	-2.027078e+01	-1.716105e+01	-2.019634e+01
1.542694e+01	7.277494e+00	2.427803e+01	-3.792439e+00	-7.872306e+00
8.932803e+00	-6.783122e+00	9.256010e+00	1.074991e+00	-1.015763e+01
-9.982780e+00	7.185765e+00	-7.823715e+00	3.203045e+00	-7.343000e+00
7.058423e+00	-7.850162e+00	-4.664589e+00	8.912042e+00	-1.493804e+01
2.942968e-01	-3.814653e+00	5.359460e+00	1.971565e-01	-1.046580e+01
-1.927508e+00	6.178566e+00	-1.363809e+01	-9.862933e+00	5.436359e+00
-1.247871e-01	7.157021e+00	-7.782824e+00	1.789796e+00	-1.592691e+01
5.082721e+00	7.561632e+00	-1.014690e+01	2.176532e+00	-1.120602e+01
-6.243958e+00	1.949352e+00	1.352516e+00	-9.117727e+00	-1.748445e+00
2.404419e+00	-8.935114e+00	5.787901e+00	-1.046367e+01	-1.107919e+01
7.586730e+00	6.139112e+00	-2.215724e+00	1.024603e+01	-2.148296e+01
-2.752629e+00	1.888175e+00	2.439854e+01	-1.299033e+01	-7.402029e+00
1.746983e+00	1.654625e+01	-2.154754e+00	-7.815860e+00	-7.883775e+00
1.197090e+00	1.598405e+00	-1.495060e+01	1.262880e+01	-1.762724e+01
-1.531169e+01	-3.837966e+00	6.780893e+00	2.158186e+01	-1.406366e+00
2.817050e+01	1.107912e+01	1.465427e+01	1.149555e+01	5.595406e-01
1.313865e+01	2.086074e+01	-1.389761e+01	-4.780710e+00	-2.211440e+01
-6.978419e+00	2.711883e+01	1.258525e+01	-8.116625e+00	1.609993e+01
4.085509e-01	6.640474e+00	-1.792557e+01	-7.039772e+00	-7.935588e+00
1.455321e+01	-5.027685e+00	4.202495e+00	1.058249e+00	-1.181780e+01
-4.307798e+00	-1.301002e+01	8.740080e+00	1.535330e+00	8.647546e-01
-7.920150e+00	7.900266e+00	-1.765888e+01	6.771135e-01	-4.401015e+00

5.329054e+00	-1.048664e+01	4.434735e+00	1.553673e+00	-1.019466e+01
-3.440457e+00	7.007790e+00	-1.686148e+01	1.234756e+01	8.147967e+00
-1.500937e+01	-7.090604e+00	1.039089e+01	-8.441939e+00	-7.038613e+00
-5.577973e+00	1.446834e+01	-7.258784e+00	-4.345025e+00	-2.445015e+00
5.640793e+00	-1.423664e+01	-5.445533e+00	8.755960e+00	3.294389e+00
-1.010157e+01	6.273735e+00	-1.102857e+01	1.076588e+01	-9.740470e+00
-9.328520e-01	2.246115e+00	4.004555e+00	1.017798e+01	-9.186220e+00
-8.776189e+00	8.456496e+00	-4.098870e+00	8.373299e+00	-5.316117e-01
6.943098e+00	-2.134519e+01	-6.058004e+00	8.566897e+00	-6.627681e+00
-1.563040e+01	3.522639e+00	1.007359e+00	2.607221e+01	9.910493e+00
2.872244e+01	-7.738468e+00	2.405164e+01	1.339754e+01	1.844684e+01
1.016407e+01	5.705628e+00	-6.869404e+00	-9.466780e+00	-2.473277e+01
-3.246551e+00	3.076594e+01	1.222248e+01	8.416312e-01	1.429302e+00
-3.106884e-01	4.787249e+00	-1.857646e+01	2.908857e-01	3.279217e+00
7.106964e+00	-1.699926e+01	1.608632e+01	-1.824448e+01	-8.492774e+00
5.947660e+00	8.198607e+00	-2.485278e+01	1.215785e+01	-7.828485e+00
-1.243306e+01	7.263334e-01	-1.761246e+01	6.354136e-01	-2.400469e+00
-1.549140e+01	1.330522e+00	-8.310662e+00	-2.858751e-02	-2.721523e+01

RESIDUAL VARIANCE = 1.212398e+02

COVARIANCE MATRIX OF ESTIMATES:

1.973300e-03	-1.591023e-03	-7.274519e-04	1.378755e-04	7.936071e-04
-2.106788e-04	-1.591023e-03	3.221223e-03	-9.083985e-04	-8.142543e-04
-5.921103e-04	7.968030e-04	-7.274527e-04	-9.083981e-04	3.161512e-03
-1.025503e-03	-7.986488e-04	1.223604e-04	1.378757e-04	-8.142539e-04
-1.025503e-03	3.165146e-03	-9.251953e-04	-7.153397e-04	7.936071e-04
-5.921111e-04	-7.986479e-04	-9.251951e-04	3.221667e-03	-1.583941e-03
-2.106787e-04	7.968032e-04	1.223602e-04	-7.153401e-04	-1.583941e-03
1.970880e-03				

STANDARD ERRORS:

4.442183e-02	5.675582e-02	5.622733e-02	5.625963e-02	5.675973e-02
4.439459e-02				

CORRELATION MATRIX OF ESTIMATES:

1.000000e+00	-6.310583e-01	-2.912462e-01	5.516880e-02	3.147521e-01
-1.068302e-01	-6.310582e-01	1.000000e+00	-2.846548e-01	-2.550074e-01
-1.838027e-01	3.162354e-01	-2.912465e-01	-2.846547e-01	1.000000e+00
-3.241847e-01	-2.502465e-01	4.901887e-02	5.516889e-02	-2.550072e-01
-3.241848e-01	1.000000e+00	-2.897318e-01	-2.864081e-01	3.147522e-01
-1.838029e-01	-2.502462e-01	-2.897317e-01	1.000000e+00	-6.285917e-01
-1.068302e-01	3.162354e-01	4.901880e-02	-2.864083e-01	-6.285914e-01
1.000000e+00				

RESIDUAL AUTOCORRELATIONS:

1.000000e+00	3.473442e-03	1.985737e-02	-3.923553e-03	5.207324e-02
3.722751e-03	2.157055e-02	-4.653008e-02	1.455601e-02	-4.472801e-02
5.233048e-02	-3.696466e-02	9.024374e-03	5.127612e-02	1.705783e-02
9.209155e-02	4.766153e-02	-4.973612e-02	4.768314e-02	-1.059030e-01
4.555550e-02	-1.138014e-01	4.626628e-02	-6.736232e-04	-2.059756e-02
1.318120e-02	-3.754254e-02	-8.796880e-02	-4.394097e-02	-3.851220e-02

7.966785e-02	-5.035416e-02	-6.580636e-02	-1.884099e-02	-1.130112e-01
-2.076864e-02	-3.354269e-02	-4.958485e-02	3.921619e-02	-7.593057e-02
2.563546e-02	-7.401919e-02	-6.940793e-02	-6.597688e-02	-3.252554e-02
7.372040e-02	-4.327371e-02	-5.277649e-02	1.597528e-02	-1.207157e-01
4.900131e-02	-4.673372e-02	-5.761386e-02	1.716637e-02	-4.443517e-02
2.659655e-02	-2.804325e-02			

CHI-SQUARE STATISTIC = 8.137434e+01

DEGREES OF FREEDOM = 50

END
DTIC
7-86